

1     **Global expansion and redistribution of *Aedes*-borne virus transmission risk**  
2                                   **with climate change**

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21

22 **Abstract:** Forecasting the impacts of climate change on *Aedes*-borne viruses—especially  
23 dengue, chikungunya, and Zika—is a key component of public health preparedness. We apply an  
24 empirically parameterized Bayesian transmission model of *Aedes*-borne viruses for the two  
25 vectors *Aedes aegypti* and *Ae. albopictus* as a function of temperature to predict cumulative  
26 monthly global transmission risk in current climates, and compare with projected risk in 2050  
27 and 2080 based on general circulation models (GCMs). Our results show that if mosquito range  
28 shifts track optimal temperatures for transmission (26-29 °C), we can expect poleward shifts in  
29 *Aedes*-borne virus distributions. However, the differing thermal niches of the two vectors  
30 produce different patterns of shifts under climate change. More severe climate change scenarios  
31 produce proportionally worse population exposures from *Ae. aegypti*, but not from *Ae.*  
32 *albopictus* in the most extreme cases. Expanding risk of transmission from both mosquitoes will  
33 likely be a serious problem, even in the short term, for most of Europe; but significant reductions  
34 are also expected for *Aedes albopictus*, most noticeably in southeast Asia and west Africa.  
35 Within the next century, nearly a billion people are threatened with new exposure to both *Aedes*  
36 spp. in the worst-case scenario; but massive net losses in risk are noticeable for *Ae. albopictus*,  
37 especially in terms of year-round transmission, marking a global shift towards more seasonal risk  
38 across regions. Many other complicating factors (like mosquito range limits and viral evolution)  
39 exist, but overall our results indicate that while climate change will lead to both increased and  
40 new exposures to vector-borne disease, the most extreme increases in *Ae. albopictus*  
41 transmission are predicted to occur at intermediate climate change scenarios.

42 **Author Summary:** The established scientific consensus indicates that climate change will  
43 severely exacerbate the risk and burden of *Aedes*-transmitted viruses, including dengue,  
44 chikungunya, Zika, West Nile virus, and other significant threats to global health security. Here,  
45 we show that the story is more complicated, first and foremost due to differences between the  
46 more heat-tolerant *Aedes aegypti* and the more heat-limited *Ae. albopictus*. Almost a billion  
47 people could face their first exposure to viral transmission from either mosquito in the worst-case  
48 scenario, especially in Europe and high-elevation tropical and subtropical regions. On the other  
49 hand, while year-round transmission potential from *Ae. aegypti* is likely to expand (especially in  
50 south Asia and sub-Saharan Africa), *Ae. albopictus* loses significant ground in the tropics,  
51 marking a global shift towards seasonal risk as the tropics eventually become too hot for  
52 transmission by *Ae. albopictus*. Complete mitigation of climate change to a pre-industrial  
53 baseline could protect almost a billion people from arbovirus range expansions; but middle-of-  
54 the-road mitigation may actually produce the greatest expansion in the potential for viral  
55 transmission by *Ae. albopictus*. In any scenario, mitigating climate change also shifts the burden  
56 of both dengue and chikungunya (and potentially other *Aedes* transmitted viruses) from higher-  
57 income regions back onto the tropics, where transmission might otherwise start to be curbed by  
58 rising temperatures.

59

## 60 **Introduction**

61 Climate change will almost certainly have a profound effect on the global distribution and  
62 burden of infectious diseases [1–3]. Current knowledge suggests that the range of mosquito-  
63 borne diseases could expand dramatically in response to climate change [4,5]. However, the  
64 physiological and epidemiological relationships between mosquito vectors and the environment  
65 are complex and often non-linear, and experimental work has showed an idiosyncratic  
66 relationship between warming temperatures and disease transmission [6,7]. In addition,  
67 pathogens can be vectored by related species, which may be sympatric, or several pathogens may  
68 be transmitted by the same vector. Accurately forecasting the potential impacts of climate change  
69 on *Aedes*-borne viruses—which include widespread threats like dengue and yellow fever, as well  
70 as several emerging threats like chikungunya, Zika, West Nile, and Japanese encephalitis—thus  
71 becomes a key problem for public health preparedness [4,8,9]. In this paper, we compare the  
72 roles and impact of two vectors, *Aedes aegypti* and *Ae. albopictus*, in their contribution to  
73 potential transmission landscapes in a changing climate.

74 The intensification and expansion of vector-borne disease is likely to be a significant  
75 threat posed by climate change to human health [2,10]. Mosquito vectors are of special concern,  
76 due to the global morbidity and mortality from diseases like malaria and dengue fever, as well as  
77 the prominent public health crises caused by (or feared from) several recently-emergent viral  
78 diseases like West Nile, chikungunya, and Zika. The relationship between climate change and  
79 mosquito-borne disease is perhaps best studied, in both experimental and modeling work, for  
80 malaria and its associated *Anopheles* vectors. While climate change could exacerbate the burden  
81 of malaria at local scales, more recent evidence challenges the “warmer-sicker world”  
82 expectation [11,12]. The optimal temperature for malaria transmission has recently been  
83 demonstrated to be much lower than previously expected [13], likely leading to net decreases in  
84 optimal habitat at continental scales in the coming decades [12].

85 Relative to malaria, less is known about the net impact of climate change on *Aedes*-borne  
86 diseases. At a minimum, the distribution of *Aedes* mosquitoes is projected to shift in the face of  
87 climate change, with a mix of expansions in some regions and contractions in others, and no  
88 overwhelming net global pattern of gains or losses [3,8]. Ecophysiological differences between  
89 *Aedes* vector species are likely to drive differences in thermal niches, and therefore different  
90 distributions of transmission risk [6,14], now and in the future. The consequences of those range

91 shifts for disease burden are therefore likely to be important, but are challenging to summarize  
92 across landscapes and pathogens. Of all *Aedes*-borne diseases, dengue fever has been most  
93 frequently modeled in the context of climate change, and several models of the potential future  
94 of dengue have been published over the last two decades, with some limited work building  
95 consensus among them [4]. Models relating temperature to vectorial capacity (the number of new  
96 infectious mosquito bites generated from a human case), and applying general circulation models  
97 (GCMs) to predict the impacts of climate change, date back to the late 1990s [5]. A study from  
98 2002 estimated that the population at risk (PAR) from dengue would rise from 1.5 billion in  
99 1990, to 5-6 billion by 2085, as a result of climate change [15]. A more recent study suggested  
100 that climate change alone should increase the global dengue PAR by 0.28 billion by 2050, but  
101 accounting for projected changes in global economic development (using GDP as a predictor for  
102 dengue risk) surprisingly reduces the projected PAR by 0.12 billion over the same interval [16].  
103 Mechanistic models have shown that increases or decreases in dengue risk can be predicted for  
104 the same region based on climate models, scenario selection, and regional variability [17].

105 Chikungunya and Zika viruses, which have emerged more recently as a public health  
106 crisis, are less well-studied in the context of climate change. A monthly model for chikungunya  
107 in Europe, constrained by the presence of *Ae. albopictus*, found that the A1B and B1 scenarios  
108 both correspond to substantial increases in chikungunya risk surrounding the Mediterranean [18].  
109 A similar modeling study found that dengue is likely to expand far more significantly due to  
110 climate change than Zika [9] (though epidemiological differences among these three viruses  
111 remain unresolved [19–21]). However, the combined role of climate change and El Niño has  
112 already been suggested as a possible driver of the 2016 Zika pandemic's severity [9]. Global  
113 mechanistic forecasts accounting for climate change are all but nonexistent for both chikungunya  
114 and Zika, given how recently both emerged as public health crises, and how much critical  
115 information is still lacking in the basic biology and epidemiology of both pathogens.

116 In this study, we apply a new mechanistic model of the spatiotemporal distribution of  
117 *Aedes*-borne viral outbreaks to resolve the role climate change could play in the emergence of  
118 diseases like dengue, chikungunya, and Zika. Whereas other mechanistic approaches often rely  
119 on methods like dynamic energy budgets to build complex biophysical models for *Aedes*  
120 mosquitoes [22,23], and subsequently (sometimes) extrapolate potential epidemiological  
121 dynamics [5], our approach uses a single basic cutoff for the thermal interval where viral

122 transmission is possible. The simplicity and transparency of the method masks a sophisticated  
123 underlying model that links the basic rate of reproduction  $R_0$  for *Aedes*-borne viruses to  
124 temperature, via experimentally-determined physiological response curves for traits like biting  
125 rate, fecundity, mosquito lifespan, extrinsic incubation rate, and transmission probability [6]. The  
126 model is easily projected into geographic space by defining model-based measures of suitability  
127 and classifying each location in space as suitable or not; we take a Bayesian approach in order to  
128 account for uncertainty in the experimental data. This threshold condition defines the  
129 temperatures at which transmission is not prevented, rather than the more familiar threshold at  
130 which disease invasion is expected ( $R_0 > 1$ , which cannot be predicted in the absence of  
131 assumptions about vector and human population sizes and other factors). We then classify each  
132 location by suitability in each month based on already published projections for current climates  
133 in the Americas [6].

134 Here, we expand the framework for both *Ae. aegypti* and *Ae. albopictus* to project  
135 cumulative months of suitability in current and future (2050 and 2080) climates, and further  
136 examine how global populations at risk might change in different climate change scenarios. We  
137 explore variation among both climate model selection (general circulation models; GCMs), and  
138 potential emissions pathways described in the IPCC AR5 (representative concentration  
139 pathways; RCPs). In doing so, we provide the first mechanistic forecast for the potential future  
140 transmission risk of chikungunya and Zika, which have been forecasted primarily via  
141 phenomenological methods (like ecological niche modeling [9]). Our study is also the first to  
142 address the seasonal aspects of population at risk for *Aedes*-borne diseases in a changing climate.

143

## 144 **Methods**

### 145 ***The Bayesian Model***

146 Our study presents geographic projections of published experimentally-derived mechanistic  
147 models of viral transmission by *Ae. aegypti* and *Ae. albopictus*. The approach to fit the thermal  
148 responses in a Bayesian framework and combine them to obtain the posterior distribution of  $R_0$   
149 as a function of these traits is described in detail in Johnson *et al.* [7] and the particular traits and  
150 fits for *Ae. aegypti* and *Ae. albopictus* are presented in Mordecai *et al.* [24]. In the original  
151 modeling study, the underlying data was compiled on transmission of dengue virus by both  
152 mosquito species, and the models for *Ae. aegypti* were subsequently validated on data compiled

153 for three viruses (dengue, chikungunya, and Zika). Once we obtain our posterior samples for  $R_0$   
154 as a function of temperature we can evaluate the probability that  $R_0 > 0$  ( $\text{Prob}(R_0 > 0)$ ) at each  
155 temperature, giving a distinct curve for each mosquito species. We then define cutoff of  $\text{Prob}(R_0$   
156  $> 0) = \alpha$  to determine our estimates of the thermal niche; here, we use  $\alpha = 0.975$ . This very high  
157 probability allows us to isolate a temperature window for which transmission is almost certainly  
158 not excluded; this provides a conservative approach. For *Ae. aegypti*, these bounds are 21.3—  
159 34.0 °C, and for *Ae. albopictus*, 19.9—29.4 °C.

160

### 161 ***Current & Future Climates***

162 Current mean monthly temperature data was derived from the WorldClim dataset  
163 ([www.worldclim.org](http://www.worldclim.org)) [25]. For future climates, we selected four general circulation models  
164 (GCMs) that are most commonly used by studies forecasting species distributional shifts, at a set  
165 of four representative concentration pathways (RCPs) that account for different global responses  
166 to mitigate climate change. These are the Beijing Climate Center Climate System Model (BCC-  
167 CSM1.1); the Hadley GCM (HadGEM2-AO and HadGEM2-ES); and the National Center for  
168 Atmospheric Research’s Community Climate System Model (CCSM4). Each of these can  
169 respectively be forecasted for RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5. RCP numbers  
170 correspond to increased radiation in  $\text{W/m}^2$  by the year 2100, therefore expressing scenarios of  
171 increasing severity. (However, even these scenarios are nonlinear over time; for example, in  
172 2050, RCP 4.5 is a more severe change than 6.0.) Climate model output data for future scenarios  
173 were acquired from the research program on Climate Change, Agriculture, and Food Security  
174 (CCAFS) web portal ([http://ccafs-climate.org/data\\_spatial\\_downscaling/](http://ccafs-climate.org/data_spatial_downscaling/)), part of the  
175 Consultative Group for International Agricultural Research (CGIAR). We used the model  
176 outputs created using the delta downscaling method, from the IPCC AR5. For visualizations  
177 presented in the main paper (Figure 2), we used the HadGEM2-ES model, the most commonly  
178 used GCM. The mechanistic transmission model was projected onto the climate data using the  
179 ‘raster’ package in R 3.1.1 (‘raster’<sup>30</sup>). Subsequent visualizations were generated in ArcMap.

180

### 181 ***Population at Risk***

182 To quantify a measure of risk, comparable between current and future climate scenarios, we used  
183 population count data from the Gridded Population of the World, version 4 (GPW4) [26],

184 predicted for the year 2015. We selected this particular population product as it is minimally  
185 modeled *a priori*, ensuring that the distribution of population on the earth's surface has not been  
186 predicted by modeled covariates that would also influence our mechanistic vector-borne disease  
187 model predictions. These data are derived from most recent census data, globally, at the smallest  
188 administrative unit available, then extrapolated to produce continuous surface models for the  
189 globe for 5-year intervals from 2000-2020. These are then rendered as globally gridded data at  
190 30 arc-seconds; we aggregated these in R to match the climate scenario grids at 5 minute  
191 resolution (approximately 10 km<sup>2</sup> at the equator). We used 2015 population count as our proxy  
192 for current, and explored future risk relative to the current population counts. This prevents  
193 arbitrary demographic model-imposed patterns emerging, possibly obscuring climate-generated  
194 change. We note that these count data reflect the disparities in urban and rural patterns  
195 appropriately for this type of analysis, highlighting population dense parts of the globe.  
196 Increasing urbanization would likely amplify the patterns we see, as populations increase overall,  
197 and the lack of appropriate population projections at this scale for 30-50 years in the future  
198 obviously limits the precision of the forecasts we provide. We thus opted for a most conservative  
199 approach. We finally subdivide global populations into geographic and socioeconomic regions as  
200 used by the Global Burden of Disease studies (**Figure S1**) [28]. We used the 'fasterize' R  
201 package [29] to convert these regions into rasters with percent (out of 100) coverage at polygon  
202 edges. To calculate population at risk on a regional basis, those partial-coverage rasters were  
203 multiplied by total population grids.

204

## 205 **Results**

206 The current pattern of suitability suggested by our model based on mean monthly temperatures  
207 (**Figure 1**) reproduces the known or projected distributions of *Aedes*-borne viruses like dengue  
208 [30], chikungunya [30], and Zika [9,32,33] well. For both *Ae. aegypti* and *Ae. albopictus*, most  
209 of the tropics is currently optimal for viral transmission year-round, with suitability declining  
210 along latitudinal gradients. Many temperate regions are suitable for up to 6 months of the year  
211 currently, but outside the areas mapped as "suitable" by previous disease-specific distribution  
212 models, or where *Aedes* mosquitoes are established; in some cases, limited outbreaks may only  
213 happen when cases are imported from travelers (e.g. in northern Australia, where dengue is not  
214 presently endemic but outbreaks happen in suitable regions [17]; or in mid-latitude regions of the



215 United States, where it has been suggested that traveler cases could result in limited  
216 autochthonous transmission [31,33]). In total, our model predicts that 6.01 billion people  
217 currently live in areas suitable for *Ae. aegypti* transmission at least part of the year (i.e., 1 month  
218 or more) and 6.33 billion in areas suitable for *Ae. albopictus* transmission.

219 Even by 2050, warming temperatures are expected to produce dramatic expansions of  
220 *Aedes* transmission risk (**Figure 2**). For *Ae. aegypti*, the pattern is fairly straightforward: major  
221 expansions of one- or two-month transmission risk in temperate regions are paired with  
222 expansion of year-round transmission in the tropics, even into the high-elevation regions that  
223 were previously protected. *Ae. albopictus* transmission risk similarly expands majorly into  
224 temperate regions, especially high latitude parts of Eurasia and North America. But the upper  
225 thermal limits to *Ae. albopictus* transmission are passed in many places, producing major  
226 reductions in regions of seasonal risk (like North Africa) and year-round suitability (northern  
227 Australia, the Amazon basin, central Africa and southern Asia). Whereas the conventional  
228 tropical-temperate gradient of mosquito-borne transmission is preserved for *Ae. aegypti*,  
229 warming becomes so severe in the tropics that year-round *Ae. albopictus* transmission risk starts  
230 to look more unfamiliar, especially in the more extreme climate pathways. By 2080, year-round  
231 suitability for transmission by *Ae. albopictus* is mostly confined to high elevation regions,  
232 southern Africa, and the Atlantic coast of Brazil; and even *Ae. aegypti* has begun to lose some  
233 core area of year-round suitability for transmission in the Amazon basin especially.

234 Globally, our models suggest a net increase in population at risk from *Aedes*-borne virus  
235 exposure, closely tracking the global rise in mean temperatures (**Figure 3**). For both mosquitoes,  
236 populations at risk of any exposure will experience a major net increase by 2050, on the order of  
237 roughly half a billion people; but even then, increases are more severe for *Ae. aegypti* than for  
238 *Ae. albopictus*. But by 2080, the differences between the mosquitoes produce a different result:  
239 while more severe warming continues to increase exposure for *Ae. aegypti*, up to nearly a billion  
240 net new exposures, the most extreme expansions for *Ae. albopictus* are in middle of the road  
241 scenarios (RCP 4.5 and 6.0). For year-round exposure, net changes tell an increasingly different  
242 story between the two mosquitoes. For *Ae. aegypti*, warming temperatures lead to a net increase  
243 of roughly 100-300 million people in areas of year-round transmission potential; in contrast, in  
244 RCP 8.5 by 2080, some parts of the tropics become so warm that even *Ae. aegypti* is no longer  
245 able to transmit. But even by 2050 in the mildest scenarios, there are drastic net losses of year-

246 round transmission potential for *Aedes albopictus*, and these only become more severe –  
247 approaching roughly 700 million – in the warmest timelines.

248 Breaking these results down by region (**Table 1 & 2**) highlights just how much regional  
249 velocity of climate change is likely to determine the future landscape of global health risks. For  
250 *Ae. aegypti*, the most notable net increases in all transmission risk are in all regions of Europe,  
251 with additional notable gains in east Asia, high-elevation parts of central America and east  
252 Africa, and the United States and Canada. But increases are expected across the board except in  
253 the Caribbean, where minor net losses are expected across scenarios and years. In contrast, for  
254 *Ae. albopictus*, more regionally-specific changes are anticipated. Major gains in Europe are again  
255 expected across the board, as well as less significant increases in central America, east Africa  
256 and east Asia, and the U.S. and Canada. But major net losses in *Ae. albopictus* transmission  
257 potential are also expected in several regions, including tropical Latin America, western Africa,  
258 south Asia and most of all southeast Asia, with a net loss of nearly 125 million people at risk by  
259 2080 in RCP 8.5. Because the upper thermal limit for *Ae. albopictus* transmission is relatively  
260 low, for western Africa and southeast Asia, the largest declines in transmission potential are  
261 expected with the largest extent of warming, while less severe warming could produce broader  
262 increases and more moderate declines in transmission potential. The difference between RCP 6.0  
263 and 8.5 is on the order of 50 and 100 million people respectively for the two regions,  
264 highlighting just how significant the degree of mitigation will be for regional health pathways.

265 For year-round transmission, the patterns are again less straightforward (**Table S1 & S2**),  
266 but overall, they highlight a global shift towards more seasonal risk for both mosquitoes,  
267 especially in the warmest scenarios. For *Ae. aegypti*, some of the largest net gains in people at  
268 risk are expected in southern Africa, with additional notable increases expected in Latin  
269 America. But even for *Ae. aegypti*, which has a very high upper thermal limit, warming  
270 temperatures exceed levels suitable for year-round transmission in some cases; for example, of  
271 all pathways, RCP 4.5 leads to the most severe increases in southern Asia. Overall, almost 600  
272 million people currently live in areas where temperatures are expected to become suitable for  
273 transmission year-round, though the net increase in year-round transmission will be much less  
274 (**Table S3**). For *Aedes albopictus*, major net losses are expected in south and southeast Asia  
275 (totaling more than 400 million people no longer at year-round risk with the most extreme  
276 warming), and additional losses are expected in east Africa and Latin America. Only the

277 southern part of sub-Saharan Africa consistently experiences net gains in year-round  
278 transmission risk; but gross increases are also expected in several regions, most of all east Africa,  
279 placing roughly 250 million people into areas of year-round transmission despite nearly triple  
280 that number in net losses.

281 We finally consider the idea of “first exposures” separately (gross gains, not accounting  
282 for losses, of any transmission risk), which may be the most epidemiologically significant form  
283 of exposure. We rank regions by these first exposures (**Table 3**), and we find that consistently  
284 the most significant new exposures are expected in Europe and east Africa for both mosquitoes.  
285 As the 2005 epidemic of chikungunya in India and the 2015 pandemic of Zika virus in the  
286 Americas highlight, arboviral introductions into naïve populations can produce atypically severe  
287 outbreaks on the order of millions of infections. This confirms fears that both Europe and East  
288 Africa may—as a consequence of climate change—be increasingly at risk from these types of  
289 black swan event outbreaks [35,36]. The current outbreak of chikungunya virus in Kenya  
290 exemplifies this expanding risk.

291

## 292 **Discussion**

293

294 The dynamics of mosquito-borne illnesses are climate-driven, and current work suggests that  
295 climate change will create massive opportunities for the expansion and intensification of *Aedes*-  
296 borne illnesses within the next century. Especially since the emergence of Zika in the Americas,  
297 many modeling studies have anticipated climate-driven emergence of dengue and chikungunya  
298 at higher latitudes [37,38] and higher elevations [39,40]. Within this literature, there have been  
299 several global studies of potential expansion [9,17,41], as well as significant focused interest in  
300 North America and Europe (perhaps reflecting geographic biases in research priorities and  
301 research institutions) [42]. The majority of this work has suggested that climate change will  
302 probably increase the global burden of morbidity and mortality from dengue and chikungunya,  
303 and therefore, that mitigation will likely improve global health outcomes [43,44]. Perhaps most  
304 concerning are fears that *Aedes*-borne viruses will be introduced into regions that have  
305 previously been unsuitable for transmission, given the potential for explosive outbreaks (like  
306 Zika in the Americas, or chikungunya in India) when viruses are first introduced into naïve  
307 populations [45]. The emergence of a Zika pandemic in the Old World [46], the establishment of

308 chikungunya in Europe beyond small outbreaks [18], or introduction of dengue anywhere the  
309 virus (or any given serotype) has not recently been found, is still a critical concern.

310 Overall, our findings support the general view that climate change will produce major  
311 expansions of *Aedes*-borne viral transmission risk. However, we also find more nuanced patterns  
312 emerging between the two species, among different climate pathways, and across localities. The  
313 largest increases in population at risk are consistently in Europe, with additional increases in  
314 high altitude regions in the tropics (eastern Africa and the northern Andes) and in the United  
315 States and Canada. These increases are expected not only for occasional exposure, but also for  
316 longer seasons of transmission, especially for *Ae. aegypti*. But mosquitoes are adapted to their  
317 existing climatic range, and while viral transmission will surely track warming temperatures into  
318 new places over some intervals, there is no reason to think warming temperatures would produce  
319 a unilateral and indefinite increase in disease transmission. Here we show that in the tropics, for  
320 *Ae. albopictus* in particular, more extreme climate pathways produce warming temperatures that  
321 exceed the suitable range for transmission in many parts of the world; and in the long term, even  
322 though total exposure may increase from both mosquitoes in our study, we predict a global shift  
323 towards seasonal regimes of exposure from *Ae. albopictus*.

324 As warming temperatures may begin to exceed the upper thermal bounds of transmission,  
325 this produces an unexpected problem in terms of climate change mitigation. Total mitigation  
326 (down to pre-industrial baselines) would presumably prevent this redistribution of global risk.  
327 But partial mitigation of climate change could keep *Ae. albopictus* mosquitoes within optimal  
328 thermal ranges for more of the year, and thereby produce worse epidemiological outcomes.  
329 Given the already insufficient response to curb carbon emissions and keep temperatures below  
330 the 2 °C target [47], models such as the ones we present here are probably most useful as a  
331 means to anticipate possible futures, depending on the degree of partial mitigation achieved.

332 These global disease futures are inherently stochastic, and the degree to which our  
333 models correspond to reality depends not only on uncertainty about climate change, but also on  
334 uncertainty about the biotic homogenization process for disease [48]. For example, reductions in  
335 transmission may be less prevalent than we expect here, as—even accounting for the velocity of  
336 climate change—viruses will probably have sufficient time to adapt to warming temperatures  
337 (within whatever evolvability they possess). Increases in transmission risk are also complicated  
338 by many factors, such as the presence or absence of *Aedes* mosquitoes, which are also

339 undergoing their own semi-independent range shifts facilitated by both climate change and  
340 human movement; our model already describes areas where *Ae. albopictus* and *Ae. aegypti* are  
341 absent but could be present in the future (and even now the ranges of these mosquitoes are not  
342 static). Whether expanding transmission risk leads to future establishment and viral outbreaks  
343 depends not only on disease introduction, but also on land use patterns and urbanization at  
344 regional scales, a fact that may ultimately buffer some high-elevation regions like the Andes  
345 from increased disease risk [49,50].

346 In addition, the applicability of these models for different combinations of vector, virus,  
347 and region depends on the nuances of vector-virus coevolution and phylogeography. The  
348 underlying data in the models we use describe dengue transmission by the two mosquitoes and  
349 can most confidently be applied to describe dengue transmission. With *Ae. aegypti*, the most  
350 commonly implicated vector of dengue, our results suggest a strong and ongoing link between  
351 warming temperatures and increased transmission [24,30]. However, the temperature-dependent  
352 transmission models were also originally validated on two additional viruses (chikungunya and  
353 Zika) and performed well, indicating coarse-scale generality. For chikungunya, the losses of *Ae.*  
354 *albopictus* transmission potential in south and southeast Asia are especially interesting; in that  
355 region, *Ae. albopictus* is especially common, and it vectors the introduced Indian Ocean lineage  
356 (IOL) of chikungunya (characterized by the E1-226V mutation, which increases transmission  
357 efficiency by *Ae. albopictus* specifically [51,52]). In south and southeast Asia, these results  
358 might suggest a decreased risk of chikungunya transmission in the worst climate scenarios.  
359 Further, multiple chikungunya introductions to Europe have been vectored by *Ae. albopictus*  
360 and/or have carried the E1-226V mutation, suggesting that *Ae. albopictus* expansion in Europe  
361 might correspond to increased chikungunya risk [51,53,54]. On the other hand, *Ae. aegypti* may  
362 be more relevant as a chikungunya vector in the Americas, given historical precedent from the  
363 explosive 2015 outbreak [51]. Finally, for Zika, a recent model that further empirically refined  
364 these predictions predicts a higher thermal minimum bound than for dengue virus; this model is  
365 an obvious target for expanding this type of climate change research, given major interest in  
366 anticipating Zika re-emergence [55].

367 In practice, these models are a first step towards an adequate understanding of potential  
368 global health futures, and the forecast horizon of these models will ultimately be determined by a  
369 number of confounding factors [56,57]. In particular, the link from transmission risk to clinical

370 outcomes is confounded by other health impacts of global change, including changing  
371 precipitation patterns, socioeconomic development, changing patterns of land use and  
372 urbanization, potential vector (and virus) evolution and adaptation to warming temperatures, and  
373 changing healthcare and vector management landscapes, all of which covary strongly  
374 (potentially leading to nonlinearities). Moreover, human adaptation to climate change may have  
375 just as much of an impact as mitigation in determining how risk patterns shift; for example,  
376 increased drought stress will likely encourage water storage practices that increase proximity to  
377 *Aedes* breeding habitat [58]. Together these will determine the burden of *Aedes*-borne outbreaks,  
378 in ways that determine the eventual relevance of the forecasts we present here.

379 Many models exist to address this pressing topic, each with different approaches to  
380 control for data limitations, confounding processes, climate model uncertainty and disease model  
381 uncertainty, different concepts of population at risk, and different preferences towards  
382 experimental, mechanistic, or phenomenological approaches. While climate change poses  
383 perhaps the most serious growing threat to global health security, the relationship between  
384 climate change and worsening clinical outcomes for *Aedes*-borne diseases is unlikely to be  
385 straightforward, and no single model will accurately predict the complex process of a global  
386 regime shift in *Aedes*-borne viral transmission. Our models only set an outer spatiotemporal  
387 bound to where transmission is thermally plausible; climate change is likely to change the risk-  
388 burden relationship at fine scales within those zones of transmission non-linearly, such that areas  
389 with shorter seasons of transmission could still experience increased overall disease burdens, or  
390 vice versa. Combining broad spatial models with finer-scale models of attack rates or outbreak  
391 size is a critical step towards bridging scales [46,59], but more broadly, research building  
392 consensus between all available models is of paramount importance [60]. This task is not limited  
393 to research on dengue and chikungunya; with several emerging flaviviruses on the horizon  
394 [61,62], and countless other emerging arboviruses likely to test the limits of public health  
395 infrastructure in coming years [63], approaches like ours that bridge the gap between  
396 experimental biology and global forecasting can be one of the foundational methods of  
397 anticipating and preparing for the next emerging global health threat.

398

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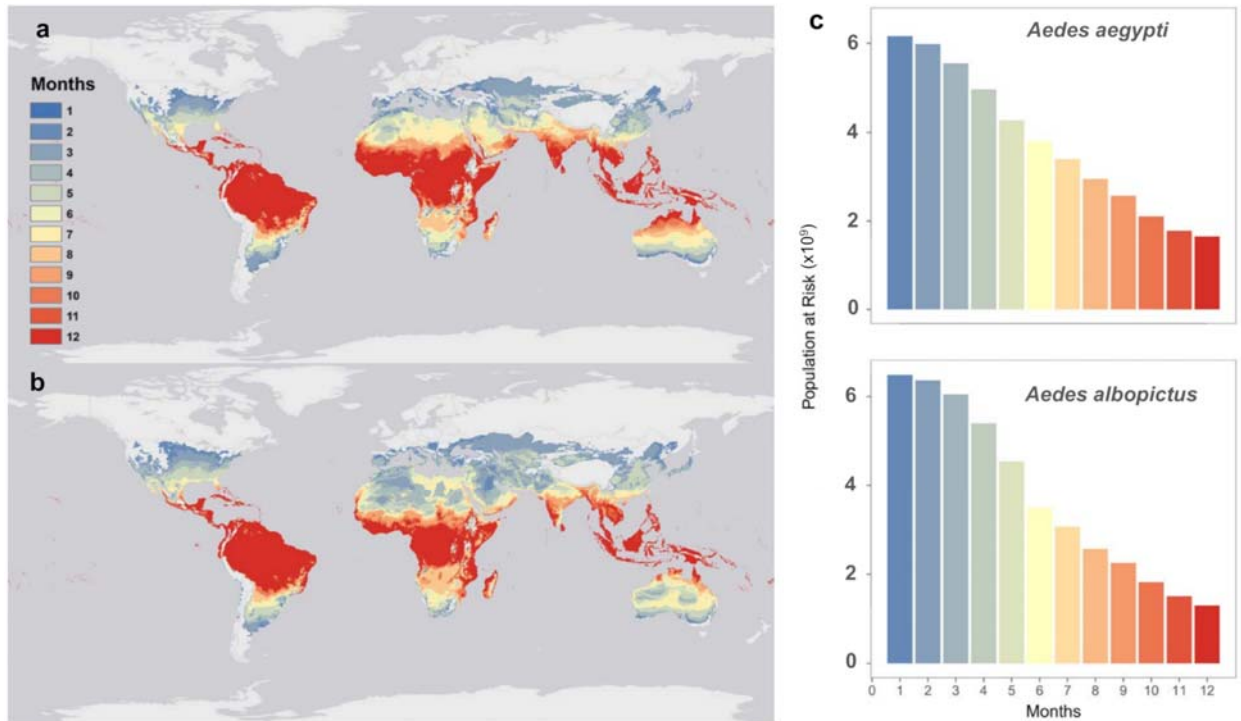
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## Figures and Tables

558 **Figure 1 | Mapping current transmission risk.** Maps of current monthly suitability based on  
559 mean temperatures for a temperature suitability threshold corresponding to the posterior  
560 probability that scaled  $R_0 > 0$  is 97.5% for (a) *Aedes aegypti* and (b) *Aedes albopictus*, and (c)  
561 the number of people at risk (in billions) as a function of their months of exposure for *Aedes aegypti*  
562 and *Aedes albopictus*.

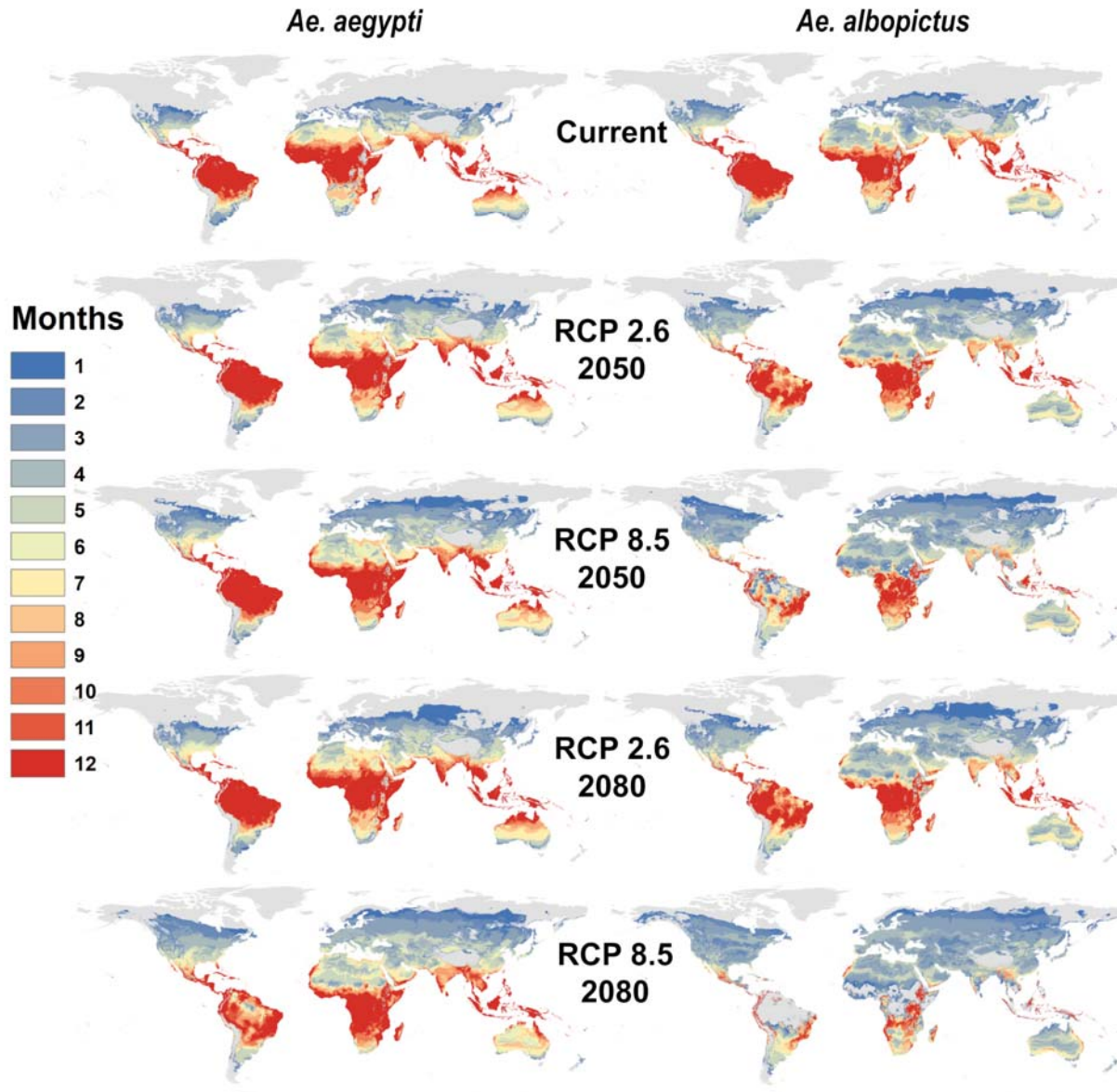
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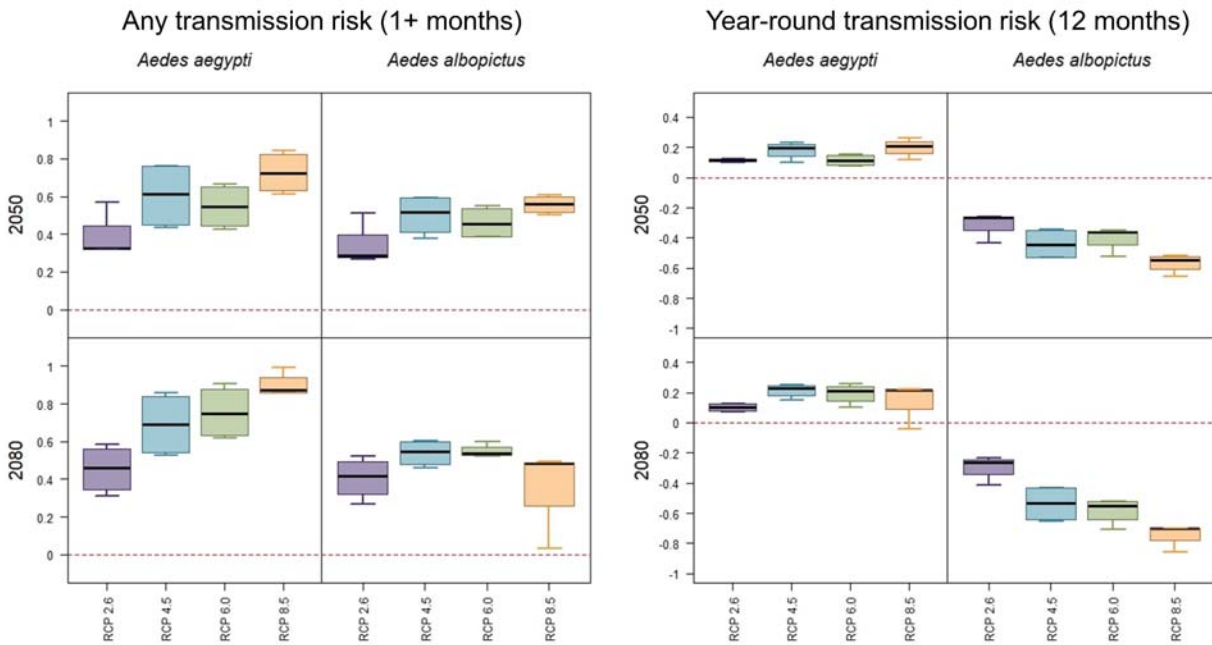
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566 **Figure 2 | Mapping future transmission risk scenarios for *Aedes aegypti* and *Aedes***  
567 ***albopictus*.** Maps of monthly suitability based on a temperature threshold corresponding to the  
568 posterior probability that scaled  $R_0 > 0$  is greater or equal to 97.5%, for transmission by *Aedes*  
569 *aegypti* and *Aedes albopictus* for predicted mean monthly temperatures under current climate and  
570 future scenarios for 2050 and 2080: RCP 2.6 and RCP 8.5 in HadGEM2-ES.



571

572 **Figure 3 | Projected net changes in population at risk.** Projections are given as the net  
573 difference in billions at risk, for *Aedes aegypti* and *Aedes albopictus* transmission,  
574 current maps and 2050 (top row) or 2080 (bottom row). Results are further broken down by  
575 representative climate pathways (RCPs), each averaged across 4 general circulation models.  
576



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580 **Table 1. Changing population at risk patterns for *Aedes aegypti*.** All values are given in  
 581 millions; future projections are averaged across GCMs, broken down by year (2050, 2080) and  
 582 RCP (2.6, 4.5, 6.0, 8.5), and are given as net change from current population at risk. 0+/0- denote  
 583 the sign of smaller non-zero values that rounded to 0.0, whereas “0” denotes true zeros.

Region	Current	2050				2080			
		2.6	4.5	6.0	8.5	2.6	4.5	6.0	8.5
Asia (Central)	69.9	8.4	10.5	9.9	12.2	8.1	11.8	12.5	15.6
Asia (East)	1,321.9	42.5	49.2	46.4	58.9	38.8	56.7	61.9	72.7
Asia (High Income Pacific)	164.0	-0.5	0+	-0.5	0.7	-0.6	0.6	1.0	1.7
Asia (South)	1,666.4	-0.1	1.6	0.7	3.7	-0.5	3.4	4.3	8.2
Asia (Southeast)	593.9	-2.1	0+	-0.6	2.3	-2.4	1.6	2.6	5.5
Australasia	12.9	3.6	5.7	5.3	6.7	4.3	6.2	6.9	8.0
Caribbean	40.4	-1.8	-1.7	-1.7	-1.6	-1.8	-1.6	-1.6	-1.5
Europe (Central)	22.7	44.2	71.8	69.0	83.3	59.0	79.3	85.5	90.6
Europe (Eastern)	41.3	57.9	110.4	93.5	133.9	80.0	124.7	130.7	156.2
Europe (Western)	114.6	47.2	132	112.0	166.8	90.3	156.4	180.8	220.9
Latin America (Andean)	31.3	2.8	3.4	3.3	4.0	2.6	3.9	4.1	5.5
Latin America (Central)	160.3	20.4	24.6	23.4	36	18.4	34.6	39.0	61.1
Latin America (Southern)	42.8	8.1	8.9	8.8	9.9	7.6	9.6	10.2	12.8
Latin America (Tropical)	181.8	19.2	19.5	19.5	19.6	18.9	19.6	19.7	19.8
North Africa & Middle East	439.5	19.7	24.1	23.8	27.2	19.3	25.9	27.3	30.3
North America (High Income)	281.9	36.2	48.3	42.6	55.0	37.8	53.6	57.1	62.8
Oceania	6.2	0.3	0.6	0.5	0.8	0.2	0.8	0.9	1.5
Sub-Saharan Africa (Central)	115.6	5.7	6.8	6.5	7.8	5.3	7.7	8.3	9.5
Sub-Saharan Africa (East)	274.8	48.8	63.7	59.1	72.2	44.7	70.8	76.6	90.9
Sub-Saharan Africa (Southern)	46.1	23.6	25.8	25.6	26.7	23.4	26.7	27.1	28.0
Sub-Saharan Africa (West)	384.0	-0.9	-0.7	-0.8	-0.7	-0.9	-0.6	-0.6	-0.4

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586

587 **Table 2. Changing population at risk patterns for *Aedes albopictus*.** All values are given in  
 588 millions; future projections are averaged across GCMs, broken down by year (2050, 2080) and  
 589 RCP (2.6, 4.5, 6.0, 8.5), and are given as net change from current population at risk. 0+/0- denote  
 590 the sign of smaller non-zero values that rounded to 0.0, whereas “0” denotes true zeros.

Region	Current	2050				2080			
		2.6	4.5	6.0	8.5	2.6	4.5	6.0	8.5
Asia (Central)	75.7	5.0	6.9	6.4	8.8	4.7	8.1	9.1	11.2
Asia (East)	1,367.0	16.1	20.8	18.9	25.2	15.0	24.0	26.5	32.4
Asia (High Income Pacific)	167.7	-2.6	-2.3	-2.6	-2.0	-2.7	-2.1	-1.9	-2.8
Asia (South)	1,673.8	-3.2	-1.7	-2.3	0+	-3.5	-0.5	-0.3	-19.1
Asia (Southeast)	602.5	-5.3	-3.8	-4.0	-6.7	-5.4	-8.5	-20.1	-124.8
Australasia	16.6	3.2	3.9	3.8	4.5	3.3	4.2	4.7	5.3
Caribbean	40.8	-1.8	-1.8	-1.8	-1.8	-1.9	-1.8	-1.8	-2.3
Europe (Central)	44.8	51.3	65.0	65.1	68.3	60.6	67.8	68.9	70.7
Europe (Eastern)	70.4	84.0	116.6	104.2	123.1	101.4	122.0	123.3	129.9
Europe (Western)	135.3	98.5	179.8	161.4	208.9	149.2	199.4	215.3	243.0
Latin America (Andean)	33.9	1.6	2.2	2.0	2.6	1.6	2.6	2.7	2.5
Latin America (Central)	179.1	21.9	27.0	27.9	31.1	17.6	29.7	30.3	23.6
Latin America (Southern)	50.4	3.2	3.6	3.6	4.8	2.8	4.2	4.9	7.6
Latin America (Tropical)	203.0	-1.5	-2.0	-1.6	-6.0	-1.5	-5.6	-8.0	-26.3
North Africa & Middle East	455.0	10.6	13.0	12.9	14.2	10.4	13.5	14.1	11.8
North America (High Income)	311.6	20.6	28.4	26.0	32.1	22.6	31.6	32.3	34.7
Oceania	6.8	0.5	0.8	0.6	1.0	0.4	0.9	1.0	0.8
Sub-Saharan Africa (Central)	120.8	2.8	3.5	3.3	4.2	2.5	4.1	4.4	-3.8
Sub-Saharan Africa (East)	320.2	30.3	39.1	36.3	42.4	27.9	41.8	42.8	34.2
Sub-Saharan Africa (Southern)	70.1	3.4	3.8	3.8	3.9	3.4	4.0	4.0	4.3
Sub-Saharan Africa (West)	384.9	-1.4	-1.5	-1.5	-2.0	-1.4	-1.9	-3.5	-59.0

591

592



593 **Table 3. Top 10 regional increases in overall transmission risk (one or more months).**  
 594 Regions are ranked based on millions of people exposed for the first time to any transmission  
 595 risk; parentheses give the net change (first exposures minus populations escaping transmission  
 596 risk). All values are given for the worst-case scenario (RCP 8.5) in the longest term (2080).

<i>Aedes aegypti</i>		<i>Aedes albopictus</i>	
1. Europe (Western)	224 (220.9)	1. Europe (Western)	246.2 (243)
2. Europe (Eastern)	156.4 (156.2)	2. Europe (Eastern)	130.1 (129.9)
3. Sub-Saharan Africa (East)	92.8 (90.9)	3. Europe (Central)	71 (70.7)
4. Europe (Central)	90.9 (90.6)	4. Sub-Saharan Africa (East)	58.1 (34.2)
5. Asia (East)	81.7 (72.7)	5. Latin America (Central)	51.9 (23.6)
6. North America (High Income)	65.7 (62.8)	6. Asia (East)	41.4 (32.4)
7. Latin America (Central)	62 (61.1)	7. North America (High Income)	37.7 (34.7)
8. North Africa & Middle East	34.3 (30.3)	8. North Africa & Middle East	19.4 (11.8)
9. Sub-Saharan Africa (Southern)	28 (28)	9. Asia (South)	12.1 (-19.1)
10. Latin America (Tropical)	21.7 (19.8)	10. Asia (Central)	11.2 (11.2)
<b>Total (across all 21 regions)</b>	<b>951.3 (899.7)</b>	<b>Total (across all 21 regions)</b>	<b>721.1 (373.9)</b>

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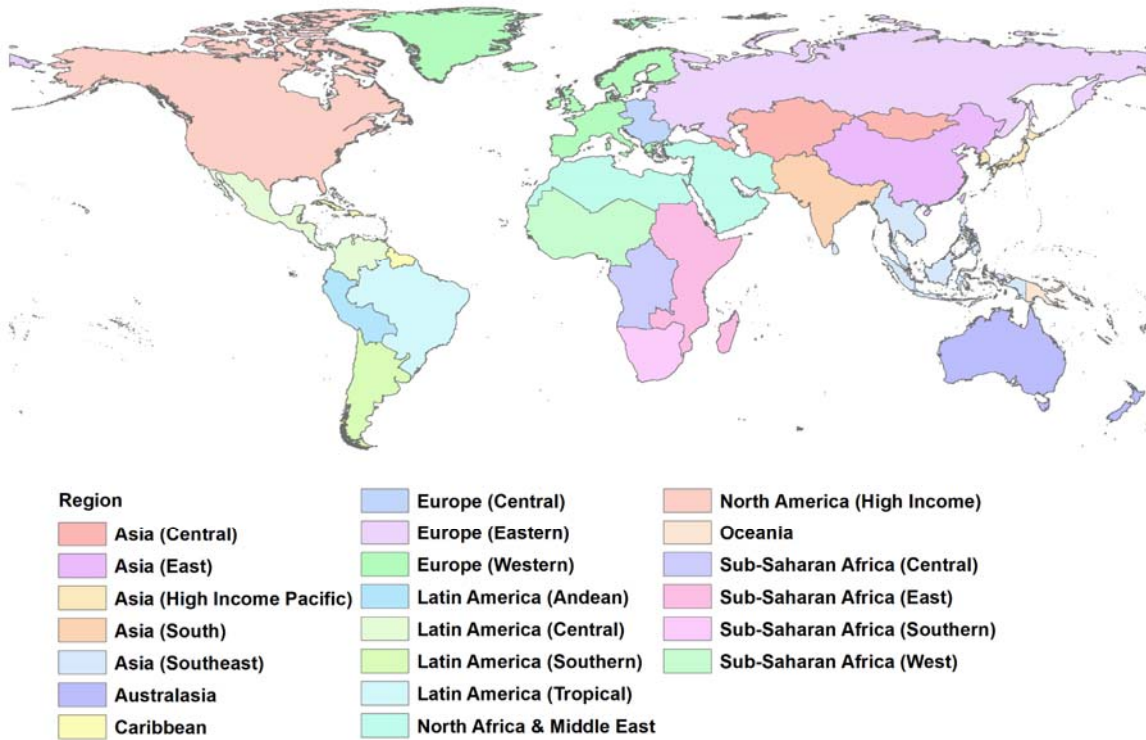
599

## Supplementary Figures & Tables

600

601 **Figure S1. Global health regions.** We adopt the same system as the Global Burden of Disease  
602 Study in our regional breakdown.

603



604

605 **Table S1. Changing year-round (12 month) population at risk patterns for *Aedes aegypti*.**  
 606 All values are given in millions; future projections are averaged across GCMs, broken down by  
 607 year (2050, 2080) and RCP (2.6, 4.5, 6.0, 8.5), and are given as net change from current  
 608 population at risk. 0+/0- denote the sign of smaller non-zero values that rounded to 0.0, whereas  
 609 “0” denotes true zeros. (Losses do not indicate loss of any transmission, only to reduction 11 or  
 610 fewer months.).

611

Region	Current	2050				2080			
		2.6	4.5	6.0	8.5	2.6	4.5	6.0	8.5
Asia (Central)	0	0	0	0	0	0	0	0	0
Asia (East)	0+	1.4	1.8	1.1	3.7	1.6	4.5	4	8.3
Asia (High Income Pacific)	3.6	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2
Asia (South)	286.4	21.8	71.8	13.7	73.6	12.1	89.7	72.6	29.6
Asia (Southeast)	499.4	19.2	22.4	19.9	25.1	18.9	26.3	15.4	-10.3
Australasia	0.2	0+	0+	0+	0.1	0+	0.2	0.2	0.3
Caribbean	34.8	1.8	2.2	2.1	2.8	1.7	2.6	2.9	3.3
Europe (Central)	0	0	0	0	0	0	0	0	0
Europe (Eastern)	0	0	0	0	0	0	0	0	0
Europe (Western)	0	0	0	0	0	0	0	0	0+
Latin America (Andean)	14.0	3.9	4.8	4.6	5.7	3.5	5.4	5.8	7.5
Latin America (Central)	88.1	13.0	18.8	17.0	25.8	12.0	24.4	27.4	34.1
Latin America (Southern)	0	0	0	0	0	0	0	0	0.2
Latin America (Tropical)	67.5	27.2	34.5	30.8	41.5	27.3	39	42.9	54.9
North Africa & Middle East	12.5	-5.2	-5.5	-6.0	-5.6	-4.7	-5.4	-5.4	-3.9
North America (High Income)	0.5	0.3	0.9	0.6	1.5	0.3	1.9	1.6	5.5
Oceania	0	0	0	0	0	0	0	0	0
Sub-Saharan Africa (Central)	5.3	0.3	0.6	0.4	0.9	0.3	0.7	0.9	1.7
Sub-Saharan Africa (East)	79.0	19.1	23.1	22.4	26.8	16.6	25.4	28.0	36.1
Sub-Saharan Africa (Southern)	126.9	43.8	60.7	56.7	78.3	37.9	74.3	85.5	110.3
Sub-Saharan Africa (West)	0	0+	0.1	0.1	0.3	0+	0.2	0.6	4.4

612

613

614

615 **Table S2. Changing year-round (12 month) population at risk patterns for *Aedes***  
 616 ***albopictus*.** All values are given in millions; future projections are averaged across GCMs,  
 617 broken down by year (2050, 2080) and RCP (2.6, 4.5, 6.0, 8.5), and are given as net change from  
 618 current population at risk. 0+/0- denote the sign of smaller non-zero values that rounded to 0.0,  
 619 whereas “0” denotes true zeros. (Losses do not indicate loss of any transmission, only to  
 620 reduction 11 or fewer months).

621

Region	Current	2050				2080			
		2.6	4.5	6.0	8.5	2.6	4.5	6.0	8.5
Asia (Central)	0	0	0	0	0	0	0	0	0
Asia (East)	1.3	1.4	-0.4	-0.5	-1	1	-0.9	-1	-1.2
Asia (High Income Pacific)	3.6	-0.3	-0.5	-0.4	-2.9	-0.2	-2.2	-3.1	-3.6
Asia (South)	98.3	-73	-80.3	-78.9	-87.3	-67.7	-86.1	-88.5	-92.6
Asia (Southeast)	435.3	-133.9	-213.3	-190.9	-277.4	-131.9	-254.8	-282.7	-343.6
Australasia	0.2	0+	0+	0+	0-	0+	0-	0-	0-
Caribbean	39.3	-5.9	-11.7	-9.4	-17.5	-4.5	-16.1	-18.1	-28.0
Europe (Central)	0	0	0	0	0	0	0	0	0
Europe (Eastern)	0	0	0	0	0	0	0	0	0
Europe (Western)	0	0	0	0	0+	0	0+	0+	0.1
Latin America (Andean)	17.9	2	0.1	0.5	-3	1.8	-2	-3.1	-5
Latin America (Central)	97.2	-23.2	-26.8	-25.3	-31.0	-20.8	-29.3	-31.4	-33.6
Latin America (Southern)	0	0	0	0	0+	0	0	0+	0+
Latin America (Tropical)	93.6	-0.8	-5.2	-6.1	-9.7	-2.9	-10.1	-12.9	-37.1
North Africa & Middle East	2.6	0+	0+	-0.2	-0.2	0.1	0-	-0.2	-0.1
North America (High Income)	1	2.8	1.4	1	0+	1.6	0.1	-0.2	-0.2
Oceania	0	0	0	0	0	0	0	0	0
Sub-Saharan Africa (Central)	5.9	0.4	0.4	0.5	0.1	0.4	0.1	0-	-1.4
Sub-Saharan Africa (East)	96.6	8.0	5.1	6.8	-4.5	7.5	-9.1	-9.9	-45.8
Sub-Saharan Africa (Southern)	133.5	31.9	38.8	38.8	43.4	29.7	39.5	43.9	39.2
Sub-Saharan Africa (West)	0+	0+	0.5	0.4	1.8	0+	0.9	2	6.2

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623

624 **Table S3. Top 10 regional increases in year-round transmission risk (12 months).** Regions  
 625 are ranked based on millions of people exposed for the first time to any transmission risk;  
 626 parentheticals give the net change (first exposures minus populations escaping transmission risk).  
 627 All values are given for the worst-case scenario (RCP 8.5) in the longest term (2080).

<i>Aedes aegypti</i>		<i>Aedes albopictus</i>	
1. Asia (South)	209.9 (29.6)	1. Sub-Saharan Africa (East)	114.3 (39.2)
2. Sub-Saharan Africa (East)	152.6 (110.3)	2. Latin America (Tropical)	39.7 (-37.1)
3. Latin America (Tropical)	63.2 (54.9)	3. Latin America (Central)	38.1 (-33.6)
4. Asia (Southeast)	44 (-10.3)	4. Sub-Saharan Africa (Central)	23.1 (-45.8)
5. Latin America (Central)	40.7 (34.1)	5. Asia (Southeast)	16.3 (-343.6)
6. Sub-Saharan Africa (Central)	36.6 (36.1)	6. Latin America (Andean)	8.6 (-5)
7. Sub-Saharan Africa (West)	8.7 (-130.2)	7. Sub-Saharan Africa (Southern)	6.2 (6.2)
8. Asia (East)	8.3 (8.3)	8. Sub-Saharan Africa (West)	2.5 (-194)
9. Latin America (Andean)	8 (7.5)	9. North Africa & Middle East	2.4 (-0.1)
10. North Africa & Middle East	7.4 (-3.9)	10. Oceania	2 (-1.4)
<b>Total</b> (across all 21 regions)	<b>597.2 (151.6)</b>	<b>Total</b> (across all 21 regions)	<b>256.5 (-740.8)</b>

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