

1    **Shifting transmission risk for malaria in Africa with climate change: a framework for**  
2    **planning and intervention**

3

4    Sadie J. Ryan<sup>1,2,3\*</sup>, Catherine A. Lippi<sup>1,2</sup>, Fernanda Zermoglio<sup>4</sup>

5

6    <sup>1</sup> Emerging Pathogens Institute, University of Florida, Gainesville, FL, USA

7    <sup>2</sup> Department of Geography, University of Florida, Gainesville, FL, USA

8    <sup>3</sup> College of Agriculture, Engineering, and Science, University of KwaZulu-Natal, Durban, South  
9    Africa

10    <sup>4</sup> Chemonics International, Washington, D.C., USA

11

12    \*Correspondence: [sjryan@ufl.edu](mailto:sjryan@ufl.edu)

13

14 **Abstract**

15 **Background:** Malaria continues to be a disease of massive burden in Africa, and the public  
16 health resources targeted at surveillance, prevention, control, and intervention comprise large  
17 outlays of expense. Malaria transmission is largely constrained by the suitability of the climate  
18 for *Anopheles* mosquitoes and *Plasmodium* parasite development. Thus, as climate changes, we  
19 will see shifts in geographic locations suitable for transmission, and differing lengths of seasons  
20 of suitability, which will require changes in the types and amounts of resources.

21 **Methods:** We mapped the shifting geographic risk of malaria transmission, in context of  
22 changing seasonality (i.e. endemic to epidemic, and vice-versa), and the number of people  
23 affected. We applied a temperature-dependent model of malaria transmission suitability to  
24 continental gridded climate data for multiple future climate model projections. We aligned the  
25 resulting outcomes with programmatic needs to provide summaries at national and regional  
26 scales for the African continent. Model outcomes were combined with population projections to  
27 estimate the population at risk at three points in the future, 2030, 2050, and 2080, under two  
28 scenarios of greenhouse gas emissions (RCP4.5 and RCP8.5).

29 **Results:** Geographic shifts in endemic and seasonal suitability for malaria transmission were  
30 observed across all future scenarios of climate change. The worst-case regional scenario  
31 (RCP8.5) of climate change places an additional 75.9 million people at risk from endemic (10-12  
32 months) exposure to malaria transmission in Eastern and Southern Africa by the year 2080, with  
33 the greatest population at risk in Eastern Africa. Despite a predominance of reduction in season  
34 length, a net gain of 51.3 million additional people will be put at some level of risk in Western  
35 Africa by midcentury.

36 **Conclusions:** This study provides an updated view of potential malaria geographic shifts in  
37 Africa under climate change for the more recent climate model projections (AR5), and a tool for  
38 aligning findings with programmatic needs at key scales for decision makers. In describing  
39 shifting seasonality, we can capture transitions between endemic and epidemic risk areas, to  
40 facilitate the planning for interventions aimed at year-round risk versus anticipatory surveillance  
41 and rapid response to potential outbreak locations.

42

43 **Keywords:** Malaria, Africa, *Anopheles*, Temperature, Climate Change

44

45 **Background**

46 Malaria causes an estimated 435,000 deaths per year, with the majority of cases occurring  
47 in Sub-Saharan Africa, affecting children under 5 disproportionately [1]. Recent advances in  
48 reducing case burdens in sub-Saharan Africa through bed net distribution, household level  
49 spraying, and rapid clinical diagnostic and treatment responses appeared to slow down in 2017  
50 and 2018, leaving reduction, and eradication goals unmet, and an estimated 219 million cases in  
51 2018 [1]. The WHO reported that for 10 high burden African countries, there was an increase of  
52 3.5 million cases in 2017 over the prior year. This stall in reduction was largely attributed to a  
53 stall in investments in global responses to malaria. The U.S. remained the single largest  
54 international donor in 2017, contributing \$1.2 billion (39% of the overall investment); it is  
55 projected that roughly \$6.6 billion annually by 2020 will be needed for the global malaria  
56 strategy, underscoring the importance of knowing how much and where to invest.

57 Geospatial modeling approaches provide a flexible framework in which to explore  
58 possible future scenarios of malaria risk as a function of changing climate [2]. Mordecai et al.  
59 introduced a mechanistic nonlinear physiological temperature-driven malaria transmission  
60 suitability model in 2013, via incorporating temperature dependent traits of both the mosquito  
61 and parasite, based on laboratory data [3]. This demonstrated that transmissibility of malaria is  
62 constrained between 17-34C, which will therefore limit the spatial distribution of malaria on the  
63 landscape. In addition, this model updated the optimum temperature for malaria transmission  
64 from 31C to 25C, and the model was well validated using 40 years of field observation data  
65 matched to specific location month and temperature [3]. Temperature has also been shown to be  
66 an important predictor of incidence in many locations [4], and the potential effects of climate-  
67 induced temperature shifts as an impact on intervention and vector control efforts have been

68 noted [5]. In previous work, we found that the top quantile of predicted transmission suitability  
69 from the Mordecai et al. model, that is, the top 25% of the transmission or  $R_0$  curve, best  
70 captured spatial and seasonal risk for Africa, from independent models of malaria risk prediction,  
71 based on statistical models of spatial case data from the Mapping Malaria Risk in Africa  
72 (MARA) and Malaria Atlas Project (MAP) projects [2,6–8].

73 Climate change threatens to alter the nature of future malaria exposure across Sub-  
74 Saharan Africa [2,6,7]. Many countries with a high burden of malaria now have weak  
75 surveillance systems and are not well positioned to assess disease distribution and trends, making  
76 it difficult to optimize responses and respond to outbreaks [9]. To date, knowledge on how  
77 climate driven changes in malaria risk will manifest at regional and national scales is limited,  
78 though such knowledge is critical to designing responses. Changes in both the areas and  
79 populations exposed to malaria risk will necessitate adaptive responses to address them. To  
80 inform these responses, we explored six scenarios of changing suitability, aligned to potential  
81 management strategies to address the changing risks. We provide an updated view of climate-  
82 driven malaria shifts in Africa from the 2015 mapping paper by Ryan et al [2], using the newer  
83 IPCC AR5 climate change scenario framework, explicitly defining season length to align with  
84 policy language, and including a sub-continental approach, aligning changes to regional scale  
85 planning.

86 The goals of this study were to (1) identify new areas that will emerge as suitable for  
87 malaria transmission under different scenarios of change; (2) identify areas that may experience  
88 reductions in transmission suitability season length; and (3) provide an estimate of the human  
89 population at risk under each scenario. These are presented in the language of malaria  
90 seasonality risk, to align with surveillance and intervention targeting goals, and summarized as

91 regional scale outcomes, broadly aligned with USAID's planning scales, as the parent aid  
92 organization of much of the US investment in the global malaria strategy.

93

94 **Methods**

95 *Malaria Transmission*

96 The model for temperature-dependent malaria transmission presented in Mordecai et al. (2013)  
97 used this expression for  $R_0$ , the basic reproductive rate of the disease, in order to account for the  
98 fitting of these rates to laboratory measurements:

$$R_0 = \sqrt{\frac{a^2 b c m p^T}{(-\ln p)r}}$$

99  
100 The temperature-dependent parameters are the mosquito biting rate (a), vector competence (b\*c),  
101 mosquito density (m), the mosquito survival rate (p), and the parasite's extrinsic incubation  
102 period (T), all of which are measurable empirical parameters.

103 The model incorporated temperature response curves fit for the mosquito species  
104 *Anopheles gambiae* and the malaria pathogen *Plasmodium falciparum*, with additional  
105 information used for related *Anopheles* and *Plasmodium* species. Transmission,  $R_0$  was scaled  
106 from 0–1, to describe relative transmission across the range of temperature. In Ryan et al [2] this  
107 curve was described this in quantiles, where the top quantile (upper 25 percent) of the curve was  
108 selected to represent the range of temperatures in which transmission suitability is expected. This  
109 conservative measure of the overall temperature curve was used as it corresponds to existing  
110 maps of ongoing transmission under current temperatures [2].

111

112 *Climate Data*

113            Current temperature data is represented by globally gridded 5 arc-minute WorldClim  
114            (version 1) monthly mean temperature data [10]. This represents a long term average, or  
115            baseline, which has been used to project future climate scenarios, and therefore serves as our  
116            baseline.

117            General Circulation Models (GCMs) are the primary source of information about  
118            potential future climate. GCMs comprise simplified but systematically rigorous mathematical  
119            descriptions of physical and chemical processes governing climate, including the role of the  
120            atmosphere, land, oceans, and biological processes. They allow for modeling the expected  
121            climate response to increasing greenhouse gas concentrations. The direct application of GCM  
122            output to adaptation decision making, however, has been relatively limited due to GCMs' coarse  
123            spatial resolution (100 to 500 km<sup>2</sup>). For strategic planning in malaria prevention and control,  
124            information is required on a much more local scale than GCMs can provide. Here, a statistically  
125            downscaled multi-model ensemble product is used for this analysis, compiled at a resolution of 5  
126            arc-minutes (~10 km<sup>2</sup>) from 6 downscaled GCMs. The climate projection data used in this study  
127            consisted of the median value for the multimodel ensemble representing future climate, compiled  
128            from the Coupled Model Intercomparison Project (CMIP5) archive, downscaled using a Change  
129            Factor (CF) approach and sourced from Navarro-Racines, Tarapues-Montenegro, and Ramírez-  
130            Villegas [11]. This ensemble approach allows exploration of the range of uncertainty across  
131            climate projections under two greenhouse gas emissions scenarios, or Representative  
132            Concentration Pathways (RCPs) – RCP 4.5 and RCP 8.5 – for three future time periods: the  
133            2030s, 2050s, and 2080s.

134

135            *Aridity Masking*

136 *Anopheles* mosquitoes (i.e., malaria-transmitting mosquitoes) require an appropriate level of  
137 moisture in their environment to provide breeding habitat with which to complete their lifecycle.  
138 Humidity or moisture is thus another component in the climate–transmission relationship. While  
139 several models use rainfall as a predictor for malaria occurrence, it is complicated to generalize  
140 how precipitation measures, such as monthly rainfall totals, cumulative rainfall, or relative  
141 humidity, actually manifest as breeding habitat for mosquitos at large scales [12–15].  
142 Precipitation may not be a good indicator of standing water, and in a world of increasingly  
143 extreme precipitation events, the difference between a month’s rainfall occurring in a single day  
144 versus gradual accumulation over that month becomes more relevant. Mosquito habitat can wash  
145 away, “flushing” away eggs and disrupting the lifecycle, meaning that more rain does not  
146 necessarily translate into more habitat [16]. In addition, much of the world is subject to  
147 agricultural irrigation, redirecting precipitation in nonlinear ways at local level, or even creating  
148 piped water environments in the absence of precipitation. To generalize habitat suitability for  
149 mosquito breeding, a remotely sensed proxy is used: the normalized difference vegetation index  
150 (NDVI), which measures the photosynthetic activity of growing plant matter, on a 0-1 scale. The  
151 NDVI is thus a useful descriptor of the type of habitat conducive to *Anopheles* breeding. The  
152 threshold of “too dry” is based on prior work conducted by Suzuki et al. [17] to exclude locations  
153 where the NDVI drops below a critical minimum level for two months of the year, thereby  
154 cutting off breeding and the transmission cycle [17]. We followed a modified version of the  
155 methods of Ryan et al. [2] to limit projected models to those geographic areas capable of  
156 supporting mosquito survival. Monthly NDVI values were derived from post-processed MODIS  
157 data, available from FEWS-Net (Famine Early Warning System Network) [18] and month-to-  
158 month thresholding was calculated [17]. That is, if the NDVI value for two consecutive months

159 fall below 0.125, it is assumed that an aridity boundary is crossed, indicating that that area  
160 (pixel) is considered too arid for malaria transmission to occur. We chose the 2016-2017 period  
161 of NDVI as an average climate year for the current decade. As NDVI cannot be projected into  
162 future scenarios, we use this as an average current aridity mask, which is a conservative  
163 approach.

164

165 *Population Data*

166 We downloaded global gridded population products, the Gridded Population of the World  
167 (GPW), at a 30 arc-second ( $\sim 1 \text{ km}^2$ ) resolution. Population data for Africa used as input for  
168 calculating population at risk (PAR) under the various transmission scenarios were derived from  
169 the Gridded Population of the World, Version 4 (GPWv4) [19], with baseline estimates derived  
170 from 2015 GPW data, while projected future populations were extracted from the 2020 layers.

171

172 *Geospatial projections of transmission*

173 The gridded temperature data (current and future climate scenarios, month-wise) were  
174 constrained to the temperature range of the optimal quantile of transmission, and the resulting  
175 number of months of transmission suitability in each pixel recorded for all of Africa. The aridity  
176 mask was applied, and pixels falling in masked areas were given no value.

177

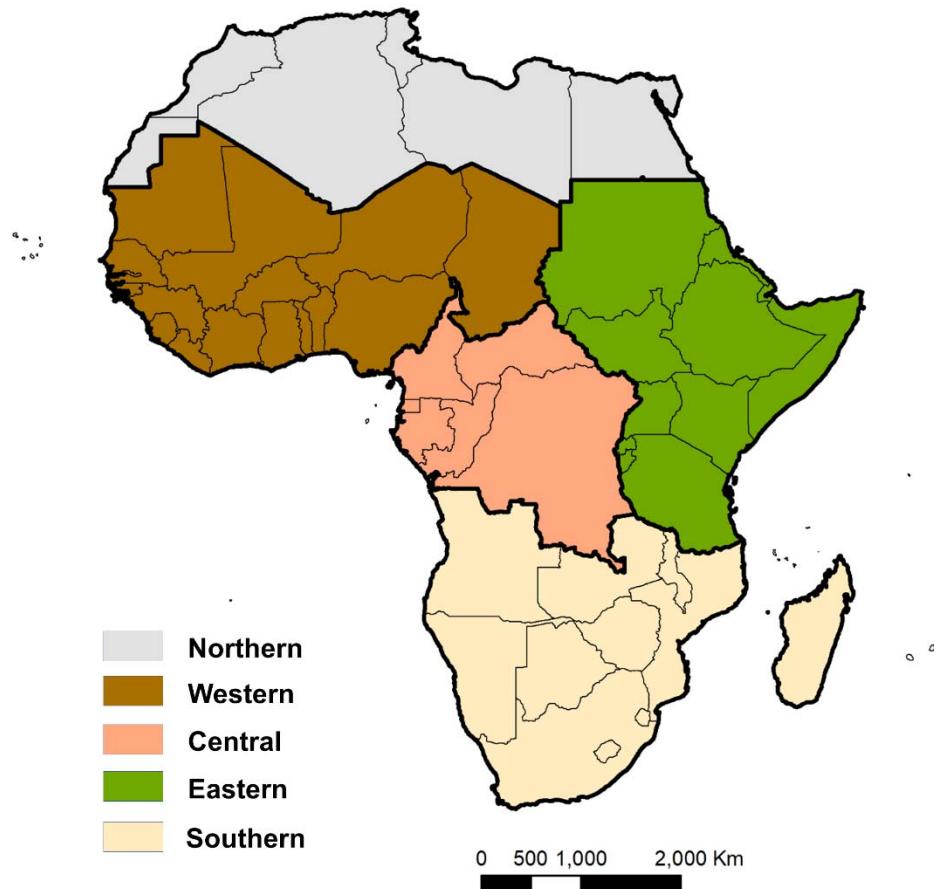
178 Seasons of transmission were defined based on the numbers of months of suitability, and  
179 criteria established by MARA were followed in defining malaria transmission suitability, with  
180 very slight additional granularity to better illustrate the impact of changing climate (Table 1).

181

182 **Table 1.** Definitions of malaria transmission suitability used in summarizing areas and  
183 population at risk.

Malaria Suitability	Definition
Endemic	Malaria transmission suitability for 10-12 months of the year
Seasonal	Malaria transmission suitability for 7-9 months of the year
Moderate	Malaria transmission suitability for 4-6 months of the year
Marginal	Malaria transmission suitability for 1-3 months of the year

184  
185 In order to estimate the population at risk (PAR) for each geospatial research question,  
186 the suitability data were aggregated by a factor of 10 and aligned to the climate data, such that all  
187 analyses were conducted at 5 arc-minute resolution (approximately 10 km<sup>2</sup> at the equator).  
188 Population data for each scenario were summarized by region, shown in Figure 1. We defined  
189 five regions of Africa; these align with the policy scale, but not definition of countries for  
190 USAID's four African regions. We chose to delineate Eastern Africa and Central Africa to align  
191 with physical geography – while USAID defines Eastern Africa to include the Democratic  
192 Republic of Congo and Congo, and Central African Republic, Cameroon, Gabon and Equatorial  
193 Guinea are all included in the USAID West African Region, we chose to define a Central Africa  
194 region, comprising these countries (Figure 1). We present results of our analyses for four of our  
195 regions, excluding Northern Africa from this study.



196

197 **Fig. 1.** Map of the five regional definitions of Africa used in this study. Note that the Northern  
198 Africa region was excluded from analyses in this study.

199

200 All calculations and analyses were conducted in R [R version 3.3.3 2017-03-06 “Another  
201 Canoe”] using the “raster,” “rgdal,” “sp,” and “maptools” packages, and mapped output was  
202 produced in ArcGIS [Version 10.5.1].

203

## 204 **Results**

205 *Regional impacts of climate change scenarios*

206 Increases in temperature by region, from baseline, for the future climate scenarios, are  
207 synthesized in Table 2. Higher future temperatures are projected under all models and time  
208 periods evaluated for the continent.

209

210 **Table 2.** Average annual temperature increases (°C) from baseline (1960–1990) by region, RCP,  
211 and time period.

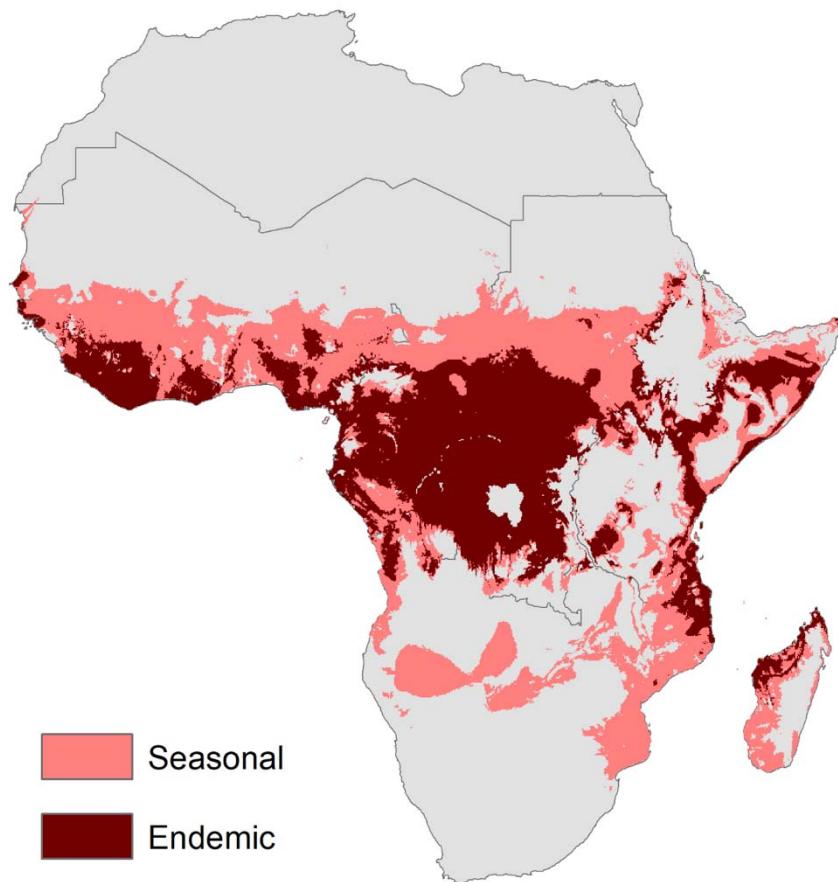
212

Region	2030s		2050s		2080s	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
West Africa	1.32	1.57	2.29	2.32	2.84	4.38
East Africa	1.32	1.63	1.90	2.32	2.96	4.38
Central Africa	1.10	1.42	1.63	2.07	2.69	4.04
Southern Africa	0.94	1.28	1.33	2.01	2.51	4.08

213

214 *Current and Future Suitability Risk*

215 Under baseline conditions, we see the current distribution of endemic (10-12 months)  
216 transmission suitability for malaria is concentrated in the Central African region, with additional  
217 areas along the southern coast of Western Africa, and along the eastern coast of Eastern Africa,  
218 and in the north of Madagascar (Figure 2). Seasonal transmission (7-9 months of the year)  
219 suitability is predicted along a band through Western and Eastern Africa, south of the areas too  
220 arid for mosquito life cycles, and in parts of Southern Africa, particularly through Mozambique.



221

222 **Fig. 2.** Modeled endemic (10-12 months) and seasonal (7-9 months) transmission suitability for  
223 malaria under current climate conditions.

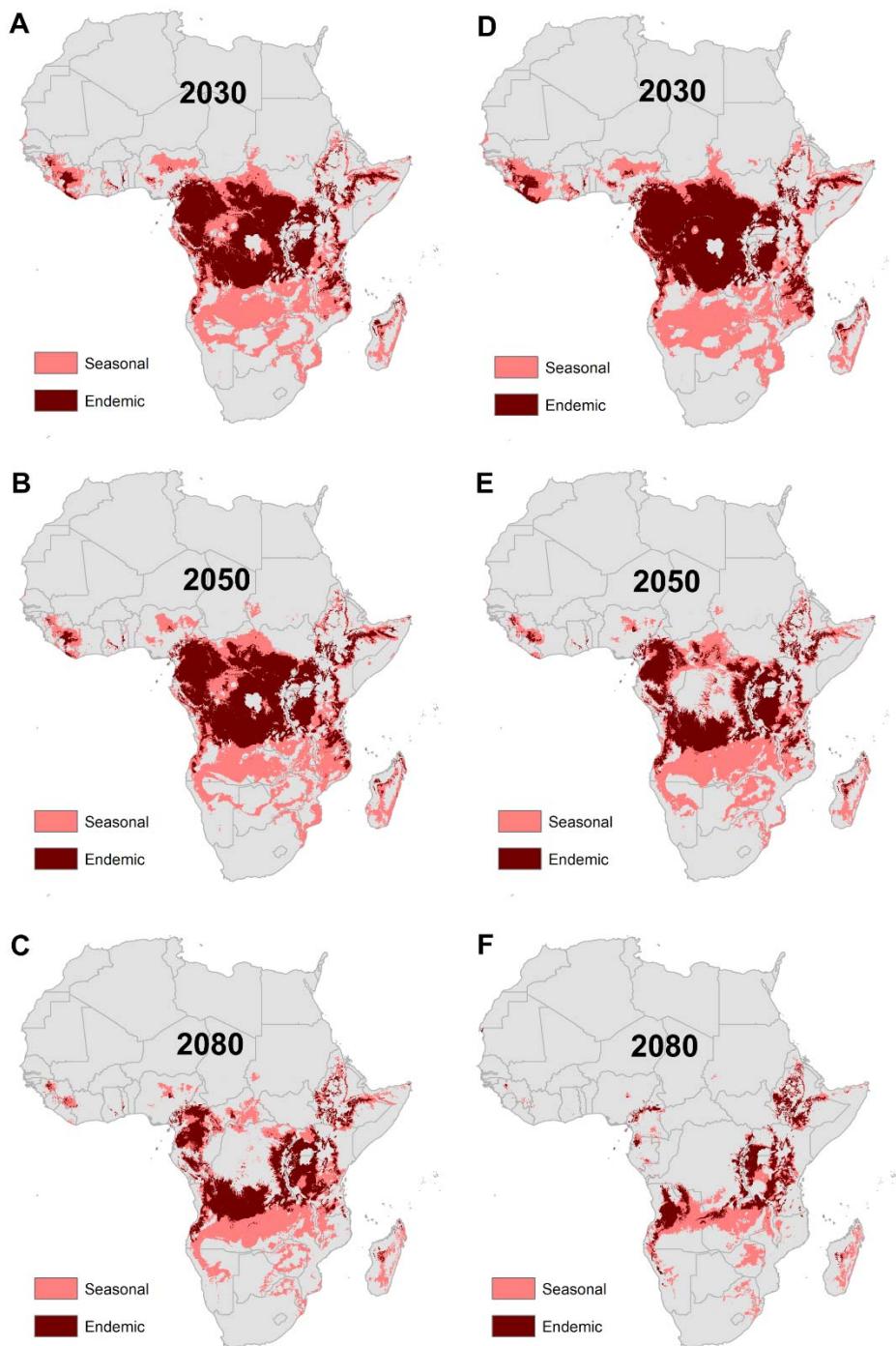
224

225 The projected future climate impacts on malaria transmission suitability are shown for  
226 both RCP 4.5 and 8.5, for the three time horizons modeled, in Figure 3. Hotspots of endemic  
227 suitability will begin to emerge in the center of the continent, the East African highlands, the  
228 Lake Victoria region, and northern Zambia, becoming more pronounced in the latter part of the  
229 21st century. A significant portion of these areas are located in Eastern Africa including Uganda,  
230 Kenya, and Tanzania, a region with currently lower suitability for endemic malaria transmission  
231 compared to Central and Western Africa. Additionally, areas predicted to have limited current  
232 suitability for *Anopheles* transmission may become seasonally suitable under conditions of a

233 changing climate, including the Southern Africa region, which will see marked increases in areas

234 suitable for seasonal and endemic malaria transmission (Figs. 2 and 3).

235



236

237 **Fig. 3.** Modeled output of malaria transmission indicates shifting future endemic (dark red) and  
238 seasonal (light red) transmission suitability under two representative concentration pathways,  
239 RCP 4.5 (A, B, C) and RCP 8.5 (D, E, F), for the years 2030, 2050, and 2080.

240

241                   Concentrated hotspots of seasonal suitability will begin to emerge in central Angola,  
242                   northwestern Zambia, northern Tanzania, and the southern coast and northern part of  
243                   Mozambique by 2030. This includes large portions of Zambia, Malawi, and Tanzania, eastern  
244                   South Africa, Botswana, the highlands of Zimbabwe, northern Mozambique, and the Zambezi  
245                   River Basin. Hotspots of seasonal malaria transmission suitability will either continue to  
246                   concentrate, or will migrate both northward and southward into the highlands of Ethiopia and  
247                   Southern Africa toward the latter part of the 21st century.

248

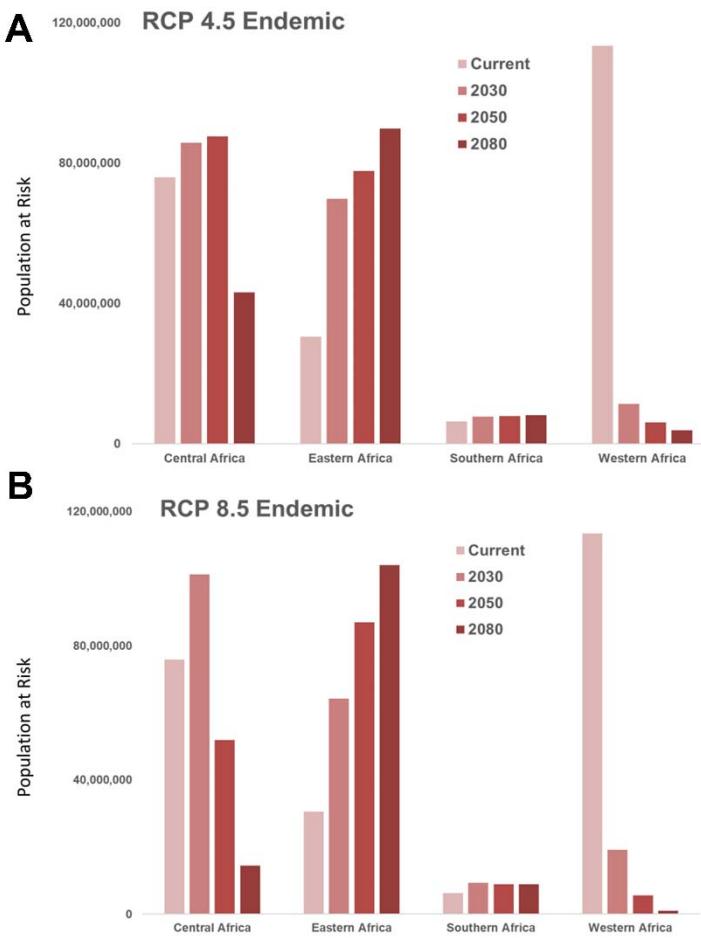
249                   *Shifting burden of transmission suitability – people at risk*

250                   An additional 196–198 million people in Eastern and Southern Africa will be burdened  
251                   with some degree of malaria transmission risk in the future due to shifting suitability by the  
252                   2080s. Regionally, by the year 2080 the worst-case scenario (RCP 8.5) places an additional 73.4  
253                   million people at risk from year-round exposure to transmission in Eastern Africa (Fig. 4). In  
254                   spite of currently low endemic suitability, shifting seasonality in Southern Africa will place over  
255                   2.5 million additional people at risk for endemic transmission by the 2080s. In the short term,  
256                   these changes are predicted to put the lives of 50.6–62.1 additional people at increased risk for  
257                   endemic transmission, and 37.2–48.2 million people at risk for seasonal transmission, throughout  
258                   Central, Eastern, and Southern Africa by the 2030s (Figs. 4 & 5). Given the strong empirical  
259                   relationship between vector survival and temperature, as temperatures rise, exposure to malaria  
260                   transmission is also expected to increase in previously unsuitable regions, such as those in the  
261                   higher elevation regions of Southern and Eastern Africa. Countries likely to be impacted by these  
262                   changes include northern Angola, southern DRC, western Tanzania, and central Uganda in 2030;

263 by 2080 these changes will extend into western Angola, the upper Zambezi River Basin, and  
264 northeastern Zambia, and will become more concentrated along the East African highlands.

265

266

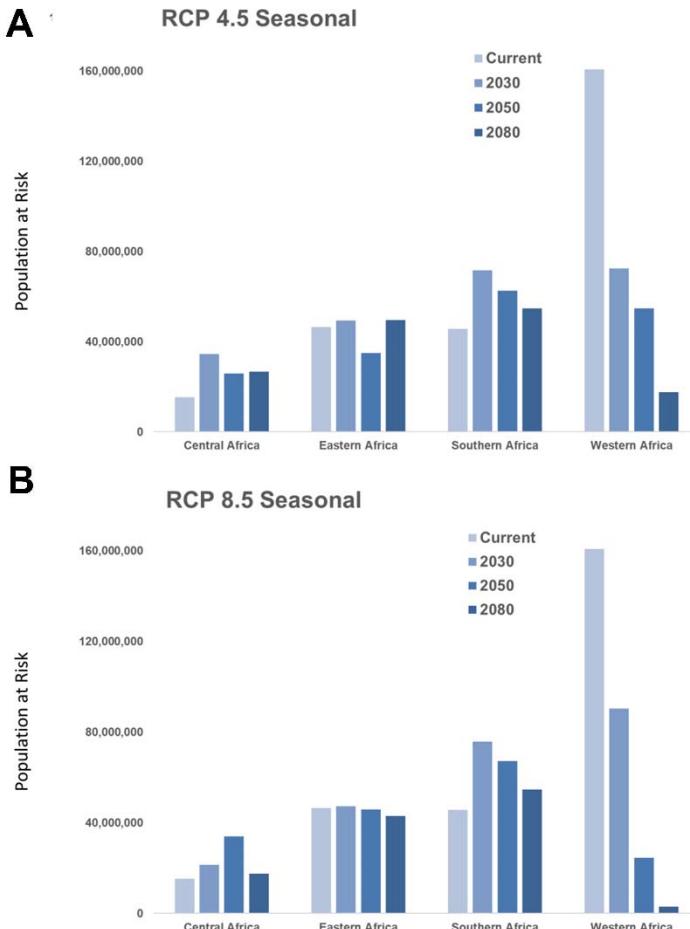


267

268 **Fig. 4.** Population at risk (PAR) for exposure to endemic malaria transmission will change in the  
269 future as geographic suitability shifts under two scenarios of climate change, RCP 4.5 (A) and  
270 RCP 8.5 (B). Eastern Africa will regionally see dramatic increases PAR by the year 2080, while  
271 shifting suitability will largely relieve the burden of endemic transmission in Western Africa.

272

273



274

275 **Fig. 5.** Population at risk (PAR) for exposure to seasonal malaria transmission will change in the  
276 future as geographic suitability shifts under two scenarios of climate change, RCP 4.5 (A) and  
277 RCP 8.5 (B). Southern Africa is predicted to have increased seasonal transmission, while shifting  
278 suitability will largely decrease seasonal transmission in Western Africa.  
279

280 These shifts in the geographic range of malaria suitability, broadly consistent across both  
281 scenarios of future climate, suggest both decreases and increases in the number of people  
282 exposed, depending on the climate scenario. The geographic and temporal evolution of future  
283 suitability of areas for malaria-transmitting *Anopheles* mosquitoes is closely tied to expected  
284 temperature changes under both RCP scenarios (Fig. 3). As temperatures rise, even within the  
285 next 12 years (by 2030), important changes are anticipated. Shifting suitability due to climate  
286 change will place additional people at risk despite reductions endemic and seasonal malaria

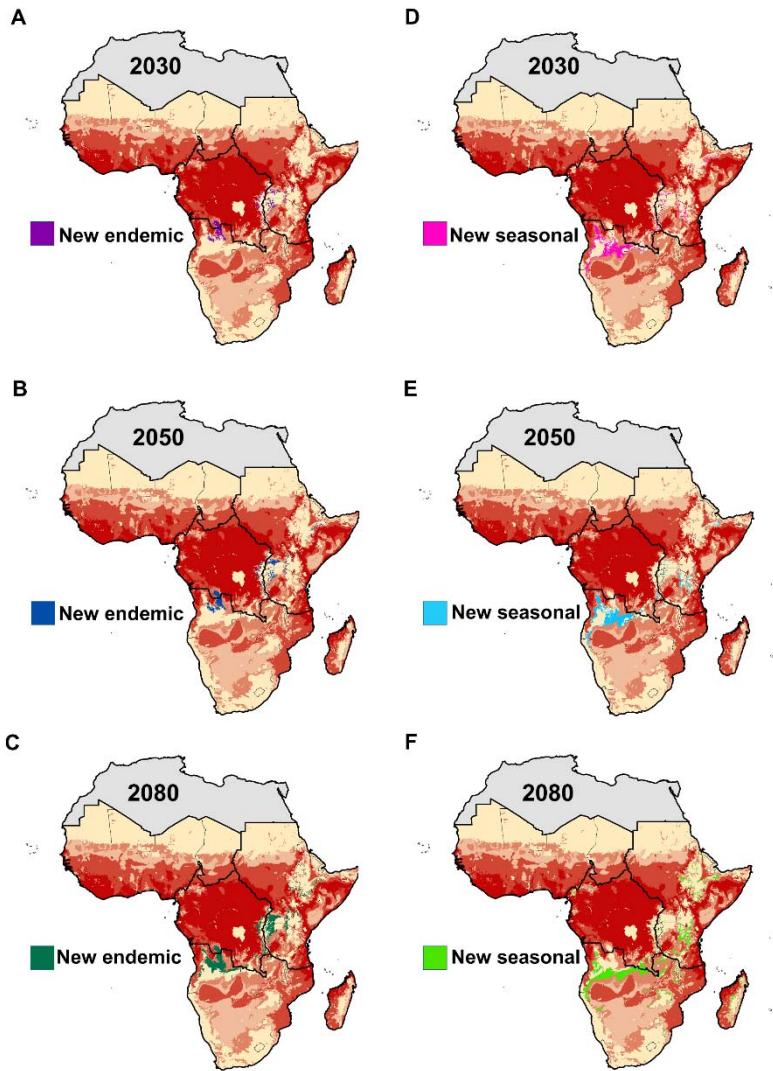
287 transmission, resulting in a net gain of 58.7 to 60.4 million people who experience some level of  
288 malaria risk in Western Africa by the 2030s. Large areas of coastal Western Africa and the Horn  
289 of Africa will likely exceed mosquitoes' thermal tolerance, with suitability disappearing. At the  
290 same time, rising temperatures will likely increase the southern range of seasonal suitability for  
291 *Anopheles* mosquitoes into Southern and Central Africa, into western Tanzania. As temperatures  
292 continue to rise (2050s), both endemic and seasonal zones will continue to exhibit an eastward  
293 shift, with thermal threshold exceedance again apparent under the worst-case scenario (RCP 8.5),  
294 eliminating suitability across Central Africa. The end-of-the-century scenarios (2080)  
295 concentrate areas of endemism in previously unsuitable or marginally suitable areas, namely the  
296 highlands of East Africa and Southern Africa. Where the number of months of suitability for  
297 *Anopheles* survival decrease, opportunities will emerge to alter and define more targeted  
298 seasonal responses, either reducing the cost of interventions or providing a window into potential  
299 eradication to malaria exposure. Targets of opportunity include Central Africa (the Central  
300 African Republic, western Congo, Cameroon, and Equatorial Guinea) and coastal East Africa  
301 (Tanzania and Kenya).

302

303 *Novel Endemic and Seasonal Risk*

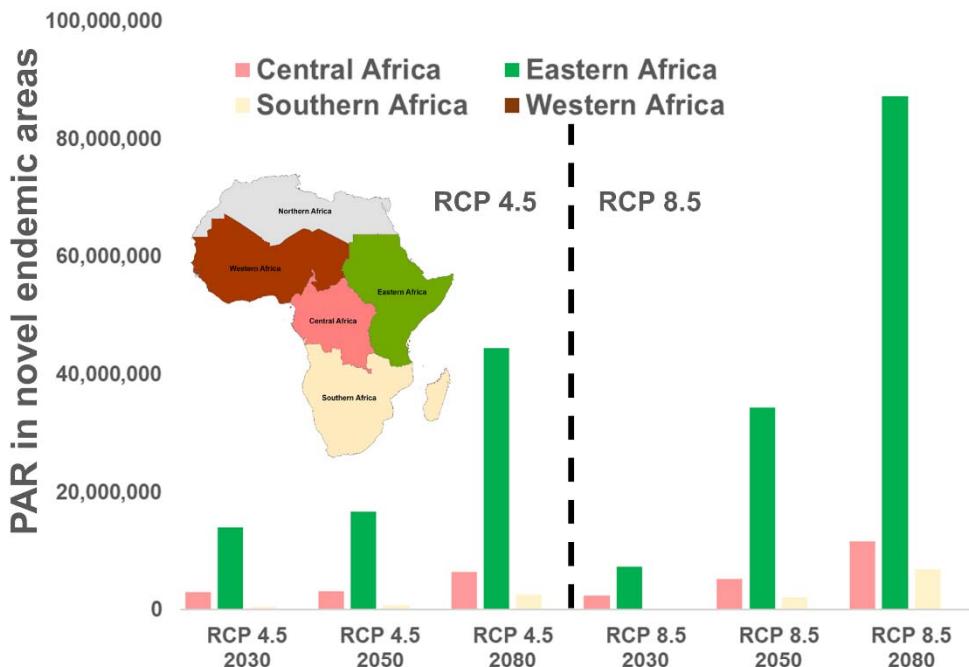
304 Some parts of Sub-Saharan Africa currently predicted to experience no malaria  
305 transmission suitability risk will experience shifting suitability, resulting in novel areas with no  
306 history of malaria transmission becoming suitable for endemic and seasonal transmission in the  
307 future. As seen in Figure 6, for RCP 4.5, this exposes populations along an arc extending into  
308 East Africa, leading to dramatic PAR increases for regional exposures, particularly novel

309 endemic exposure increase in East Africa, and novel seasonal exposures in Southern Africa  
310 (Figure 7).

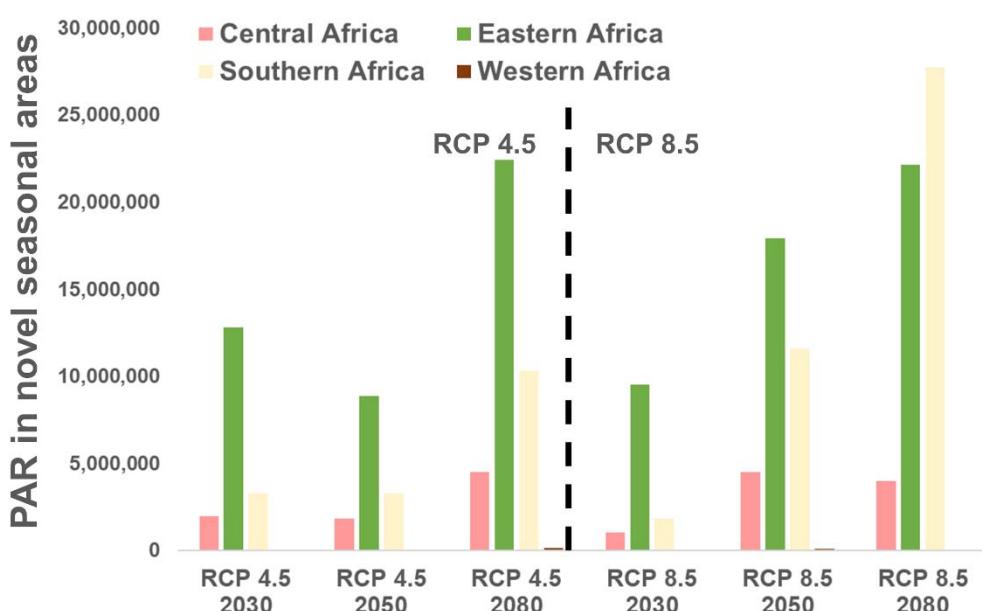


311  
312 **Figure 6:** New areas of endemic (A-C) and seasonal (D-F) suitability, under RCP 4.5 for 2030,  
313 2050, and 2080. Red shading intensity indicates current malaria suitability season.  
314

A



B



315

316 **Figure 7:** The number of people at risk (PAR) in A. newly endemic (10-12 month) suitable  
317 areas, and B. newly seasonal (7-9 month) suitable areas, for RCP 4.5 and RCP 8.5, in 2030,  
318 2050, 2080

319

## 320 Discussion

321 The changes in the geographic range of malaria suitability, broadly consistent across both  
322 scenarios of future climate, suggest that the number of people exposed to conditions of malaria

323 suitability will both increase and decrease in Sub-Saharan Africa, depending on the region. Thus,  
324 as some populations experience reduced burden of malaria risk in the future, shifting suitability  
325 will increasingly place naïve populations at risk for outbreaks, particularly in Southern and  
326 Central Africa. Malaria outbreaks that occur where people have little or no immunity to the  
327 disease can lead to epidemic conditions, especially among vulnerable groups such as women and  
328 children [1,20]. This research identifies “hotspots” where current exposure, and therefore  
329 immunity, is nonexistent; these areas could see epidemic “flares” as climate conditions affect  
330 vector survival and reproduction. This effect may be further exacerbated in novel areas with no  
331 previous history of malaria exposure, where both immunity and knowledge regarding malaria  
332 prevention are lacking [21–23]. Malaria outbreaks occurring where people have acquired  
333 immunity due to prolonged and repeated malaria exposure trigger management actions  
334 employing a cadre of tools, including vector control and case management approaches to prevent  
335 or reduce transmission [23,24].

336 These results enable us to pinpoint regions where interventions need to be revisited to  
337 consider how climate will alter risk profiles in the future. The strong seasonal cycle of malaria  
338 across Southern Africa is related to climate and weather conditions [25,26]. Thus, during some  
339 periods of the year, climate conditions are not conducive to spread of the disease. Given the  
340 strong empirical relationship between vector survival and temperature, as temperatures rise  
341 exposure to malaria transmission is expected to increase in previously unsuitable regions, such as  
342 those in the higher elevation regions of Southern and East Africa. A key concern with climate  
343 change impacts is whether climate change will lengthen the period of the year during which  
344 diseases can establish and be transmitted. For example, areas where spring and autumn are now  
345 too cold for the reproduction of malaria vectors may become more suitable in the future. In these

346 areas, increases in temperature may not impact midsummer malaria incidence greatly, but may  
347 result in a longer season, extending into both spring and autumn, during which malaria  
348 incidences will occur. In some cases, malaria may shift from being a seasonal disease burden to a  
349 year-round burden. This will necessitate different types of management and control interventions  
350 than those currently in place for short-season malaria [27,28]. Where the number of months of  
351 suitability for *Anopheles* survival decreases, opportunities will emerge to alter and define more  
352 targeted seasonal responses – either reducing the cost of interventions or providing a window  
353 into potential eradication to malaria exposure. An increase in the number of months where  
354 conditions are suitable for mosquito survival will require responses to be extended for longer  
355 periods of time, increasing resource needs (e.g. staff time, medicines) as well as costs [29]. In  
356 examining areas where malaria suitability is currently considered seasonally restricted, but will  
357 likely become more prevalent throughout the year, public health planners can anticipate which  
358 regions may require an extended investment pipeline.

359 A fundamental underpinning of modeling the response of vector-borne diseases to  
360 climate and ecology is the choice of model process. Previous approaches, such as that of the  
361 Malaria Atlas Project (MAP) and the Mapping Malaria Risk in Africa (MARA) project, are  
362 essentially top-down, wherein empirical data collected on the ground are matched to local  
363 climate conditions, and suitability established via geostatistical methods. In contrast, the  
364 modeling approach used here is mechanistic and “bottom-up,” wherein the life history of  
365 mosquitoes and pathogens, and their responses to temperature, are explicitly quantified based on  
366 empirical, laboratory-based data and incorporated into the model to predict where suitability for  
367 transmission is likely to occur. A mechanistic model, built independently of case outcome data,

368 allows for validation with empirical, field-collected data, and obviates the bias of modeling data  
369 while intervention is ongoing, as is inevitably the case with previous approaches [30].

370 While substantial progress has been made in recent years in the provision and use of  
371 climate projections, considerable uncertainties remain with their use [31]. Using climate science  
372 research results to inform the decision process about which policies or specific measures are  
373 needed to tackle climate impacts requires acknowledging the uncertainties inherent in climate  
374 projections. These uncertainties may arise from mathematical reductions (parameterizations) of  
375 climate phenomena; potential socioeconomic technological pathways and attendant carbon cycle  
376 feedbacks that influence atmospheric concentrations of key greenhouse gases; imperfect  
377 scientific knowledge and the computational constraints of modelling regional detail while still  
378 incorporating relevant large-scale climate patterns; and the relationship between climate models  
379 and their relative impacts on key sectors and resources [31–33]. Furthermore, uncertainty can  
380 arise over the chance of a single event (for example, crossing a threshold), recurrent events (the  
381 return period of a flood, for example), discrete events (hurricane frequency), and complex events  
382 (for example, the interplay of different factors that lead to drought) [34]. Recognizing this, good  
383 practice is followed by incorporating a multimodel range of climate projections rather than a  
384 single model, as performed in this study [31,35,36]. For the population data specifically, it is  
385 important to recognize that the projected population for 2020 is used to calculate the numbers of  
386 people potentially affected by changing suitability conditions across all future time periods. As  
387 with climate models, these projections do not necessarily capture all of the factors that drive  
388 population movement and growth and should be taken as best modelled estimates rather than  
389 exact values.

390        The study results are based on the temperature response curves of both *Anopheles*  
391        mosquitoes and malaria pathogens. Nevertheless, many studies point to the critical role that  
392        rainfall plays in vector survival across Sub-Saharan Africa [12,14,15]. For example, single,  
393        intense rainfall events can wash away critical breeding sites, leading to a reduction in  
394        transmission potential [16,37]. Similarly, too little rainfall can limit mosquito survival as  
395        moisture is a prerequisite for breeding habitat [38]. The approach herein addresses this second  
396        issue by masking out areas that are too arid for mosquito survival. While the relationship  
397        between rainfall and *Anopheles* survival is critical, the available projections of rainfall are  
398        uncertain at the geographic scale of this work and therefore are not considered in this analysis.

399        Geographically projected model outputs are a useful component of a planning and  
400        intervention framework, providing a means of communicating key areas of risk and affected  
401        populations to decisionmakers. Anticipation of not only the location and time, but the duration of  
402        potential outbreak events will facilitate the development of efficient and timely agency  
403        responses. Moreover, this framework serves as a foundation for scenario analysis, explicitly  
404        modeling risk of exposure for different climate scenarios and time horizons. The range of  
405        potential outcomes allows governments and agencies the flexibility needed to reasonably  
406        anticipate resource use and funding needs, enabling the development of adaptive intervention  
407        strategies for both near and long-term outcomes.

408

## 409        **Conclusions**

410        Addressing the changing risk profiles projected in this suitability analysis will require  
411        modifying current interventions and programs and implementing new ones to explicitly consider  
412        climate variability and change. Opportunities for improved responses also exist, including

413 detailed geographic targeting, optimizing strategies and seasonal alignment with interventions.

414 Identifying high risks in new areas of suitability present opportunities for informed action.

415 Where malaria suitability is currently nonexistent to newly suitable, whether seasonal or

416 endemic, the risks are critical, especially given that local populations' immunity will be low.

417 This could lead to the potential emergence of novel strains, rapid resistance, and untimely

418 identification, translating into epidemic outbreaks. To respond, targeted and informed geographic

419 surveillance in these regions could help to prepare timely responses before epidemic outbreaks

420 occur. Knowing where and when more people will potentially be exposed offers an opportunity

421 to increase the investment timeframe (seasonal to year-round), optimize vector control, and

422 improve case management, with the evidence base to support these actions. Moving down the

423 path toward elimination for some regions, where malaria transmission suitability decreases,

424 opportunities will arise to focus resources on making surveillance and response systems

425 increasingly sensitive and focused to identify, track, and respond to malaria cases and any

426 remaining transmission foci.

427

## 428 **Abbreviations**

429 **MAP:** Malaria Atlas Project

430 **MARA:** Mapping Malaria Risk in Africa

431 **NDVI:** normalized difference vegetation index

432 **GCM:** global climate model

433 **CMIP5:** Coupled Model Intercomparison Project

434 **CF:** change factor

435 **RCP:** representative concentration pathway

436 **PAR:** population at risk

437 **GPW:** Gridded Population of the World

438

439 **Declarations**

440 **Availability of Data and Materials**

441 Data sharing is not applicable to this article as no datasets were generated or analysed during the  
442 current study.

443 **Competing Interests**

444 The authors declare no competing interests

445 **Consent for Publication**

446 Not applicable

447 **Ethics Approval and Consent to Participate**

448 Not applicable

449 **Funding**

450 This analysis was funded by the United States Agency for International Development through  
451 the Adaptation Thought Leadership and Assessments (ATLAS) Task Order No. AID-OAA-I-14-  
452 00013, under the Restoring the Environment through Prosperity, Livelihoods, and Conserving  
453 Ecosystems (REPLACE) IDIQ.

454

455 **Authors' Contributions**

456 SJR and FZ conceived of the study, SJR ran analyses, FZ, SJR, and CAL wrote, edited, and  
457 refined the manuscript

458

459 **Acknowledgements**

460 The authors would like to thank Tegan Blaine and Colin Quinn of USAID's Africa bureau for  
461 their guidance in aligning the assessment to on the ground management decisions; and Jordan  
462 Burns and Rene Salgado of the President's Malaria Initiative for the review and comments.

463

464 **References**

- 465 1. World Health Organization. World Malaria Report 2018. 2018 Nov p. 210.
- 466 2. Ryan SJ, McNally A, Johnson LR, Mordecai EA, Ben-Horin T, Paaijmans K, et al. Mapping  
467 Physiological Suitability Limits for Malaria in Africa Under Climate Change. *Vector-Borne and*  
468 *Zoonotic Diseases*. 2015;15:718–25.
- 469 3. Mordecai EA, Paaijmans KP, Johnson LR, Balzer C, Ben-Horin T, de Moor E, et al. Optimal  
470 temperature for malaria transmission is dramatically lower than previously predicted. Thrall P,  
471 editor. *Ecology Letters*. 2013;16:22–30.
- 472 4. Pascual M, Ahumada JA, Chaves LF, Rodo X, Bouma M. Malaria resurgence in the East  
473 African highlands: temperature trends revisited. National Acad Sciences; 2006.
- 474 5. Siraj AS, Santos-Vega M, Bouma MJ, Yadeta D, Carrascal DR, Pascual M. Altitudinal  
475 Changes in Malaria Incidence in Highlands of Ethiopia and Colombia. *Science*. 2014;343:1154–  
476 8.
- 477 6. Tanser FC, Sharp B, le Sueur D. Potential effect of climate change on malaria transmission in  
478 Africa. *The Lancet*. 2003;362:1792–8.
- 479 7. Gething PW, Smith DL, Patil AP, Tatem AJ, Snow RW, Hay SI. Climate change and the  
480 global malaria recession. *Nature*. 2010;465:342–5.
- 481 8. Gething P, Van Boeckel T, Smith D, Guerra C, Patil A, Snow R, et al. Modelling the global  
482 constraints of temperature on transmission of *Plasmodium falciparum* and *P. vivax*. *Parasites &*  
483 *Vectors*. 2011;4:92.
- 484 9. Binka F, De Savigny D. MONITORING FUTURE IMPACT ON MALARIA BURDEN IN  
485 SUB-SAHARAN AFRICA. *The American Journal of Tropical Medicine and Hygiene*.  
486 2004;71:224–31.
- 487 10. Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A. Very high resolution interpolated  
488 climate surfaces for global land areas. *International Journal of Climatology*. 2005;25:1965–78.
- 489 11. Navarro Racines CE, Tarapues Montenegro JE, Thornton P, Jarvis A, Ramirez Villegas J.  
490 CCAFS-CMIP5 Delta Method Downscaling for monthly averages and bioclimatic indices of  
491 four RCPs [Internet]. World Data Center for Climate (WDCC) at DKRZ; 2019 [cited 2019 May  
492 2]. Available from: [http://cera-www.dkrz.de/WDCC/ui/Compact.jsp?acronym=CCAFS-CMIP5\\_downscaling](http://cera-www.dkrz.de/WDCC/ui/Compact.jsp?acronym=CCAFS-CMIP5_downscaling)
- 494 12. Thomson MC, Mason SJ, Phindela T, Connor SJ. Use of rainfall and sea surface temperature  
495 monitoring for malaria early warning in Botswana. *Am J Trop Med Hyg*. 2005;73:214–21.
- 496 13. Grover-Kopec E, Kawano M, Klaver RW, Blumenthal B, Ceccato P, Connor SJ. An online  
497 operational rainfall-monitoring resource for epidemic malaria early warning systems in Africa.  
498 *Malar J*. 2005;4:6.

499 14. Pascual M, Cazelles B, Bouma MJ, Chaves LF, Koelle K. Shifting patterns: malaria  
500 dynamics and rainfall variability in an African highland. *Proc Biol Sci.* 2008;275:123–32.

501 15. Craig MH, Snow RW, le Sueur D. A climate-based distribution model of malaria  
502 transmission in sub-Saharan Africa. *Parasitol Today (Regul Ed).* 1999;15:105–11.

503 16. Paaijmans KP, Wandago MO, Githeko AK, Takken W. Unexpected High Losses of  
504 Anopheles gambiae Larvae Due to Rainfall. Carter D, editor. *PLoS ONE.* 2007;2:e1146.

505 17. Suzuki R, Xu J, Motoya K. Global analyses of satellite-derived vegetation index related to  
506 climatological wetness and warmth. *International Journal of Climatology.* 2006;26:425–38.

507 18. US Geological Survey and US Agency for International Development. FEWS-NET (Famine  
508 Early Warning Systems Network) [Internet]. 2018 [cited 2018 Jan 19]. Available from:  
509 <https://earlywarning.usgs.gov/fews/search/Africa>

510 19. Center For International Earth Science Information Network-CIESIN-Columbia University.  
511 Gridded Population of the World, Version 4 (GPWv4): Population Density Adjusted to Match  
512 2015 Revision of UN WPP Country Totals [Internet]. Palisades, NY: NASA Socioeconomic  
513 Data and Applications Center (SEDAC); 2016 [cited 2018 Mar 8]. Available from:  
514 [http://beta.sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-adjusted-to-2015-  
515 unwpp-country-totals](http://beta.sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-adjusted-to-2015-unwpp-country-totals)

516 20. Trape J-F, Rogier C. Combating malaria morbidity and mortality by reducing transmission.  
517 *Parasitology Today.* 1996;12:236–40.

518 21. Ndyomugenyi R, Magnussen P, Clarke S. Malaria treatment-seeking behaviour and drug  
519 prescription practices in an area of low transmission in Uganda: implications for prevention and  
520 control. *Transactions of the Royal Society of Tropical Medicine and Hygiene.* 2007;101:209–15.

521 22. Doolan DL, Dobano C, Baird JK. Acquired Immunity to Malaria. *Clinical Microbiology  
522 Reviews.* 2009;22:13–36.

523 23. Kiszewski AE, Teklehaimanot A. A review of the clinical and epidemiologic burdens of  
524 epidemic malaria. *Am J Trop Med Hyg.* 2004;71:128–35.

525 24. Abeku TA. Response to Malaria Epidemics in Africa. *Emerging Infectious Diseases.*  
526 2007;13:681–6.

527 25. Adeola A, Botai J, Rautenbach H, Adisa O, Ncongwane K, Botai C, et al. Climatic Variables  
528 and Malaria Morbidity in Mutale Local Municipality, South Africa: A 19-Year Data Analysis.  
529 *International Journal of Environmental Research and Public Health.* 2017;14:1360.

530 26. Ikeda T, Behera SK, Morioka Y, Minakawa N, Hashizume M, Tsuzuki A, et al. Seasonally  
531 lagged effects of climatic factors on malaria incidence in South Africa. *Scientific Reports*  
532 [Internet]. 2017 [cited 2019 Sep 20];7. Available from: <http://www.nature.com/articles/s41598-017-02680-6>

534 27. Walker PGT, Griffin JT, Ferguson NM, Ghani AC. Estimating the most efficient allocation  
535 of interventions to achieve reductions in *Plasmodium falciparum* malaria burden and  
536 transmission in Africa: a modelling study. *The Lancet Global Health*. 2016;4:e474–84.

537 28. World Health Organization. WHO Policy Recommendation: Seasonal Malaria  
538 Chemoprevention (SMC) for *Plasmodium falciparum* malaria control in highly seasonal  
539 transmission areas of the Sahel sub-region in Africa [Internet]. Global Malaria Program, World  
540 Health Organization; 2012. Available from:  
541 [https://www.who.int/malaria/publications/atoz/smc\\_policy\\_recommendation\\_en\\_032012.pdf?ua=1](https://www.who.int/malaria/publications/atoz/smc_policy_recommendation_en_032012.pdf?ua=1)

543 29. Goodman C, Coleman P, Mills A. Cost-effectiveness of malaria control in sub-Saharan  
544 Africa. *The Lancet*. 1999;354:378–85.

545 30. Mordecai EA, Caldwell JM, Grossman MK, Lippi CA, Johnson LR, Neira M, et al. Thermal  
546 biology of mosquito-borne disease. Byers J (Jeb), editor. *Ecology Letters*. 2019;22:1690–708.

547 31. Knutti R, Sedláček J. Robustness and uncertainties in the new CMIP5 climate model  
548 projections. *Nature Climate Change*. 2013;3:369–73.

549 32. Raäisaänen J. How reliable are climate models? *Tellus A: Dynamic Meteorology and*  
550 *Oceanography*. 2007;59:2–29.

551 33. Knutti R, Allen MR, Friedlingstein P, Gregory JM, Hegerl GC, Meehl GA, et al. A Review  
552 of Uncertainties in Global Temperature Projections over the Twenty-First Century. *Journal of*  
553 *Climate*. 2008;21:2651–63.

554 34. Palmer TN, Shutts GJ, Hagedorn R, Doblas-Reyes FJ, Jung T, Leutbecher M.  
555 REPRESENTING MODEL UNCERTAINTY IN WEATHER AND CLIMATE PREDICTION.  
556 *Annual Review of Earth and Planetary Sciences*. 2005;33:163–93.

557 35. Knutti R, Abramowitz G, Collins M, Eyring V, Glecker P, Hewitson B, et al. Good Practice  
558 Guidance Paper on Assessing and Combining Multi Model Climate Projections. IPCC Working  
559 Group I Technical Support Unit; 2010.

560 36. Meehl GA, Covey C, Delworth T, Latif M, McAvaney B, Mitchell JFB, et al. THE WCRP  
561 CMIP3 Multimodel Dataset: A New Era in Climate Change Research. *Bulletin of the American*  
562 *Meteorological Society*. 2007;88:1383–94.

563 37. Zermoglio F, Ryan SJ, Swaim M. Shifting burdens: malaria risk in a hotter Africa. USAID;  
564 2019.

565 38. Charlwood JD, Kihonda J, Sama S, Billingsley PF, Hadji H, Verhave JP, et al. The rise and  
566 fall of *Anopheles arabiensis* (Diptera: Culicidae) in a Tanzanian village. *Bulletin of*  
567 *Entomological Research*. 1995;85:37–44.

568