

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

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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 km²). 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 km²) 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

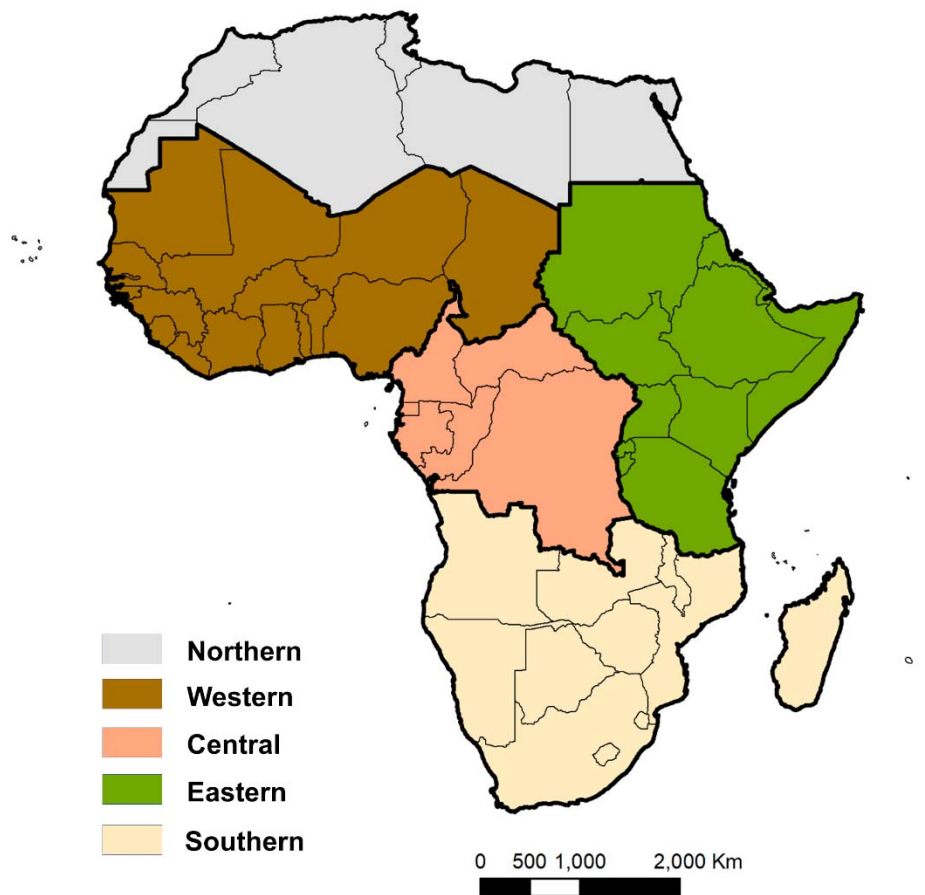
178 Seasons of transmission were defined based on the numbers of months of suitability, and
179 criteria established by MARA were followed in defining malaria transmission suitability, with
180 very slight additional granularity to better illustrate the impact of changing climate (Table 1).

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 km² 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.

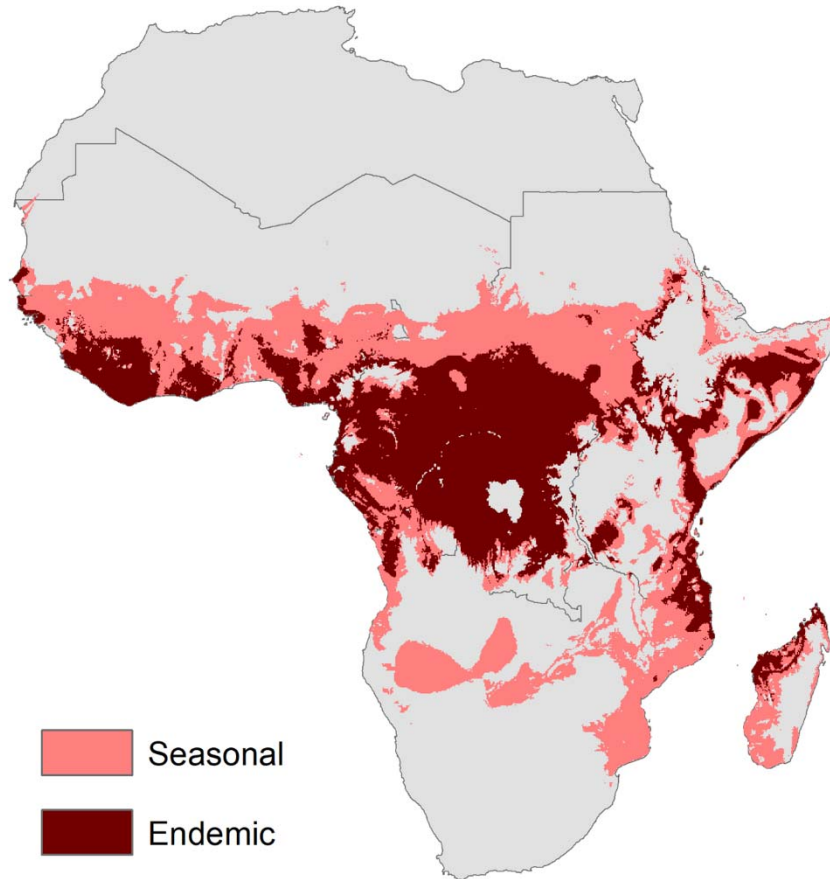
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Region	2030s		2050s		2080s	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
West Africa	1.32	1.57	2.29	2.32	2.84	4.38
East Africa	1.32	1.63	1.90	2.32	2.96	4.38
Central Africa	1.10	1.42	1.63	2.07	2.69	4.04
Southern Africa	0.94	1.28	1.33	2.01	2.51	4.08

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.



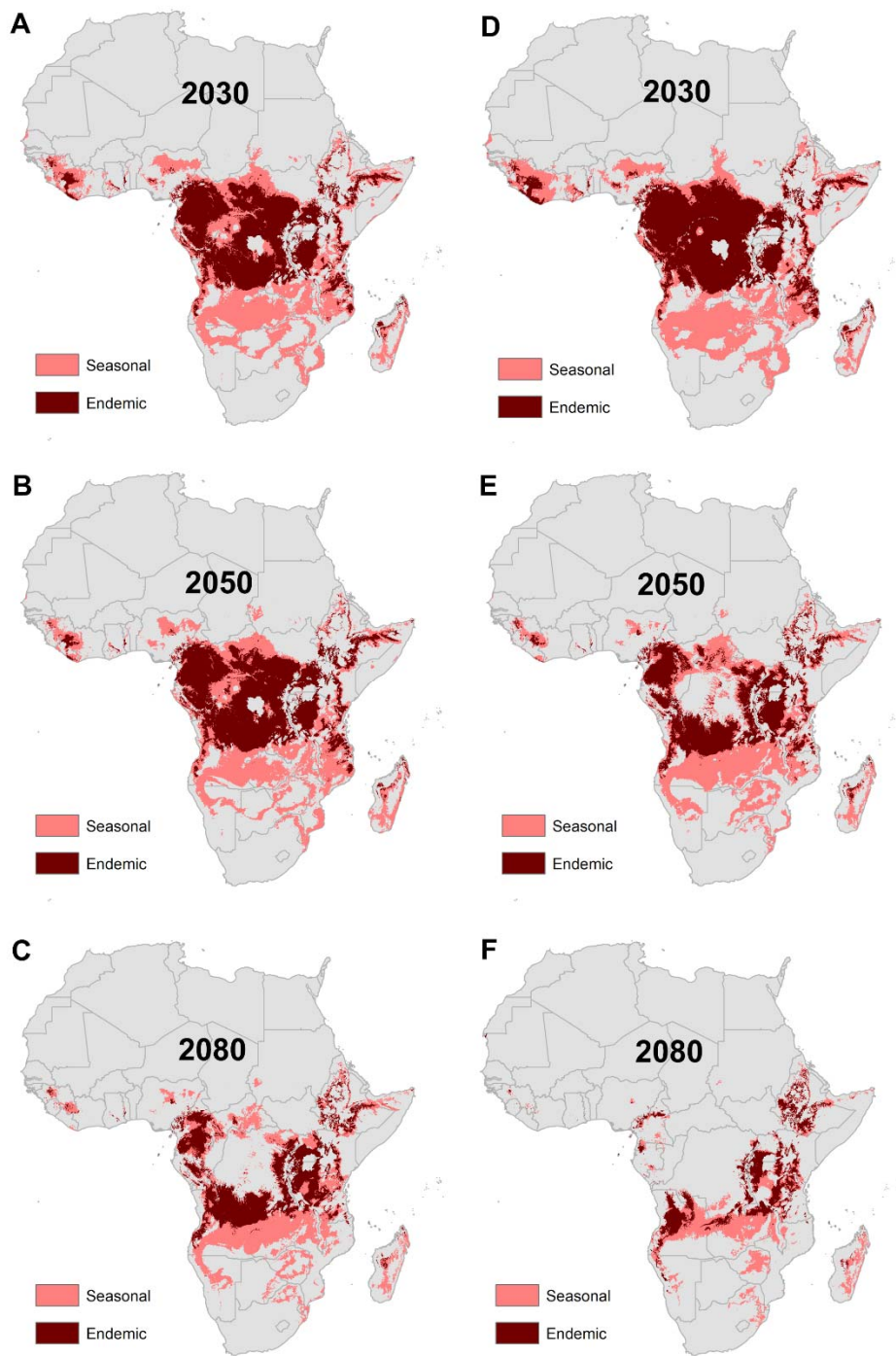
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222 **Fig. 2.** Modeled endemic (10-12 months) and seasonal (7-9 months) transmission suitability for
223 malaria under current climate conditions.

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.

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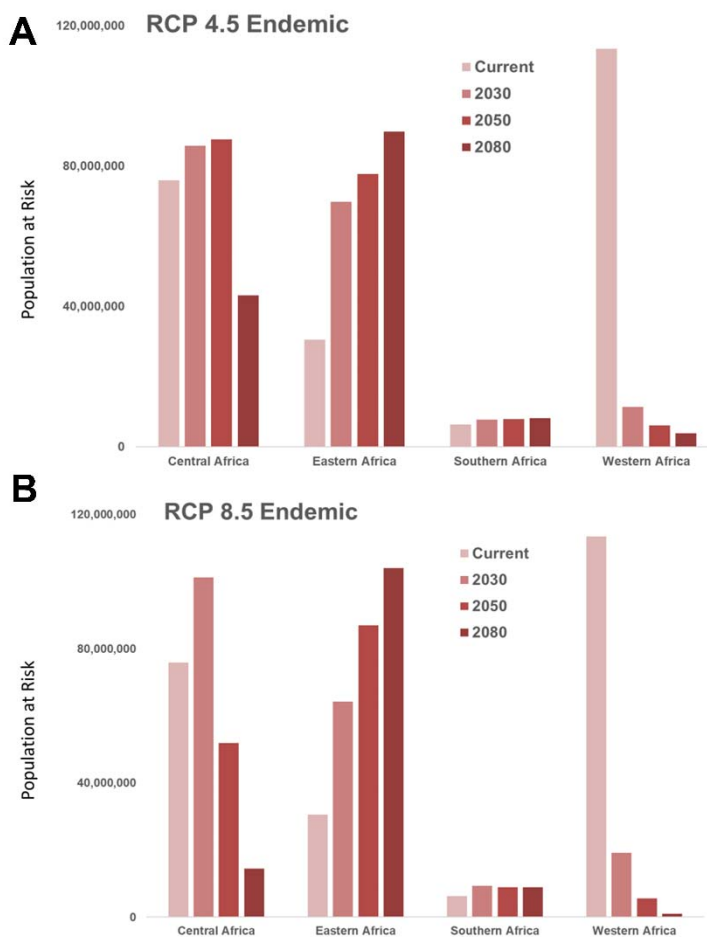
241 Concentrated hotspots of seasonal suitability will begin to emerge in central Angola,
242 northwestern Zambia, northern Tanzania, and the southern coast and northern part of
243 Mozambique by 2030. This includes large portions of Zambia, Malawi, and Tanzania, eastern
244 South Africa, Botswana, the 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.

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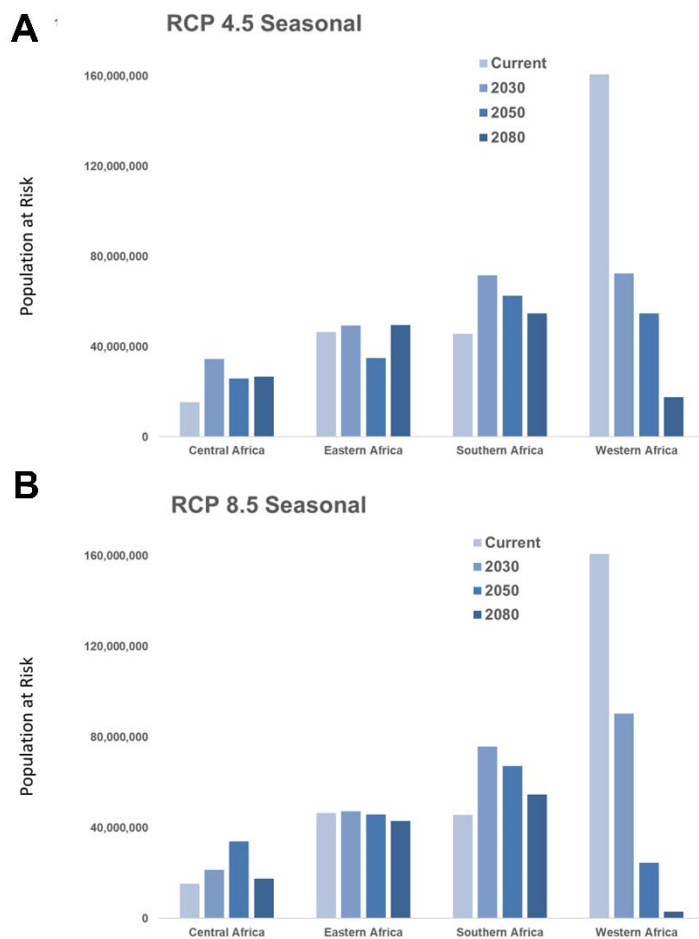
249 *Shifting burden of transmission suitability – people at risk*

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

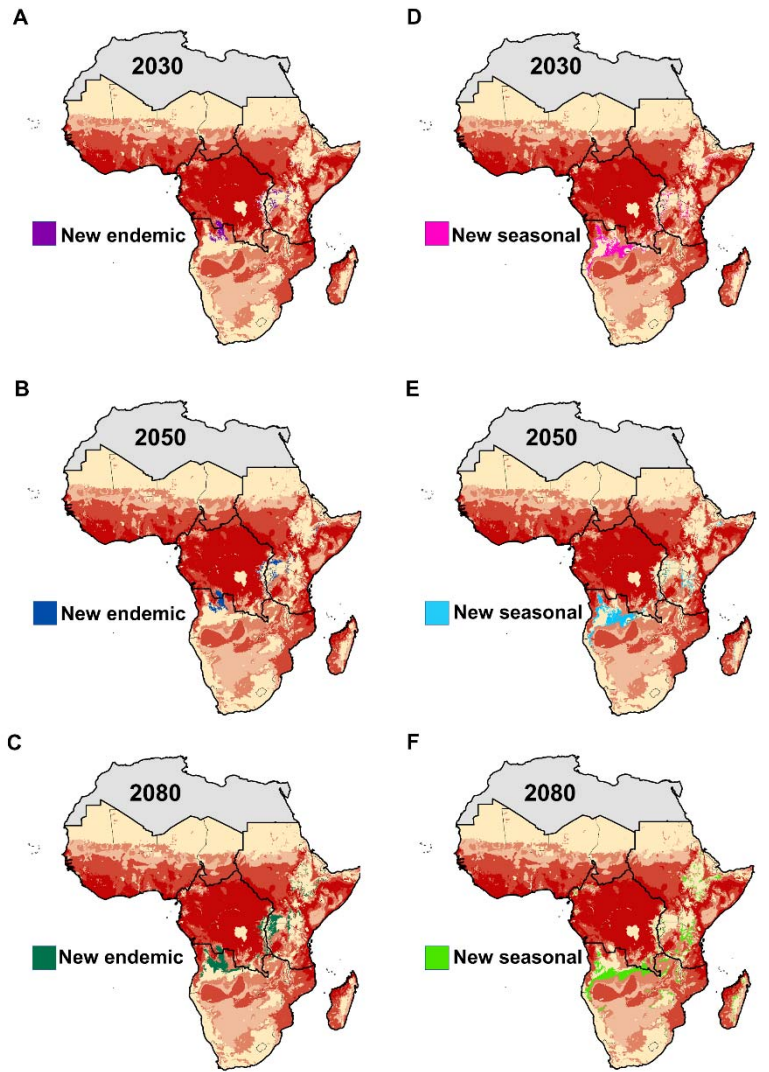
287 transmission, resulting in a net gain of 58.7 to 60.4 million people who experience some level of
288 malaria risk in Western Africa by the 2030s. Large areas of coastal Western Africa and the Horn
289 of Africa will likely exceed mosquitoes' thermal tolerance, with suitability disappearing. At the
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

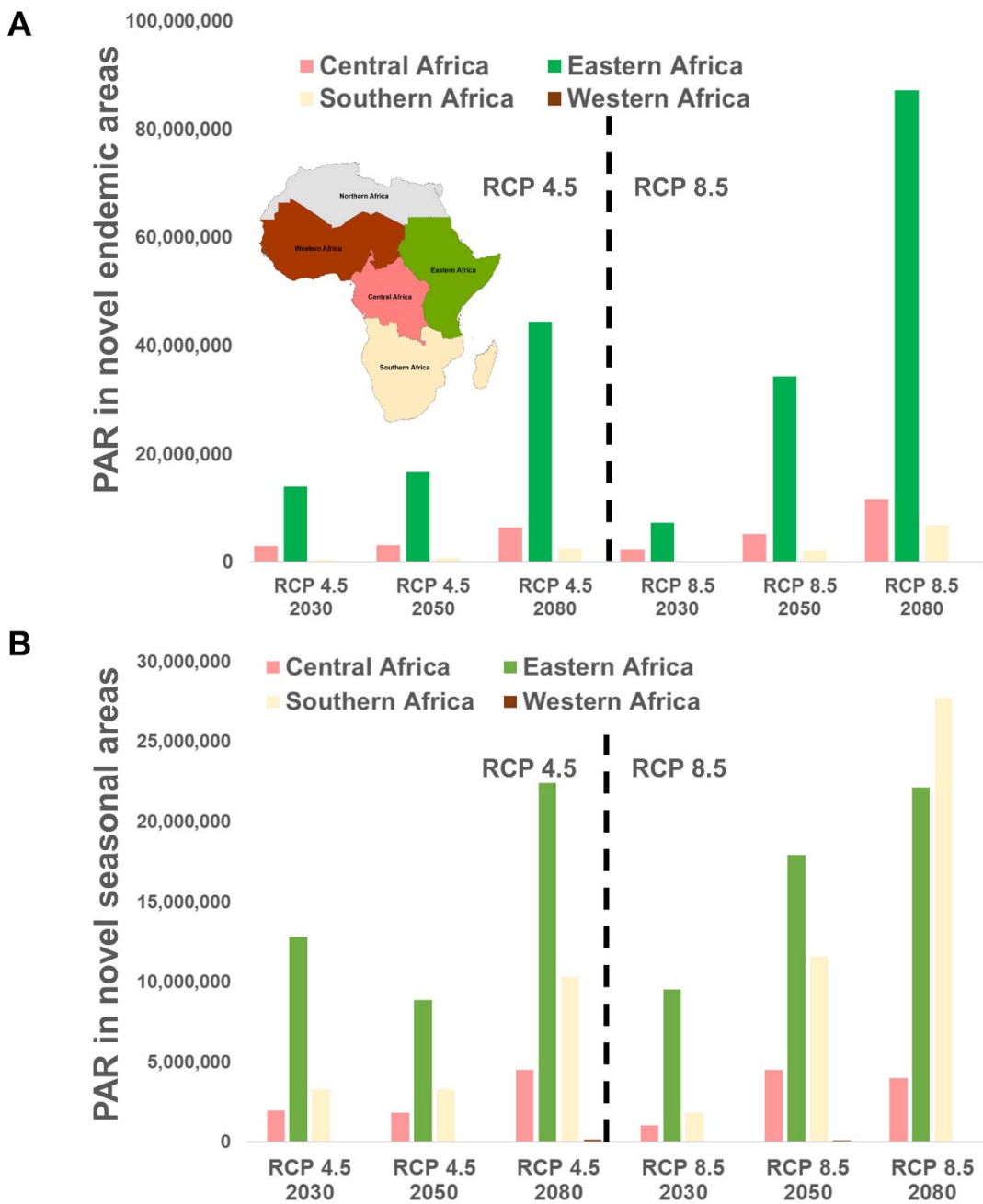
303 *Novel Endemic and Seasonal Risk*

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



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**

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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

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463

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