

# Modeling Climate-Induced Changes in Vectorial Capacity of Malaria Vectors for Enhanced Vector Surveillance and Control

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## 2 ABSTRACT

Malaria remains a significant threat to Sub-Saharan Africa, where approximately 94% of malaria cases and deaths occur. Ghana, however, has made strides in reducing malaria prevalence and fatalities through its National Malaria Elimination Programme (NMEP), which sets ambitious targets: achieving a 100% reduction in mortality by 2028 and halving cases compared to 2022 figures. Crucial to attaining these goals is a data-driven approach, particularly in strengthening malaria surveillance. Unfortunately, Ghana's current surveillance system is inadequate, mainly reliant on healthcare facility-based reporting, which has limitations such as underrepresentation of rural areas and the knowledge gaps among healthcare providers. Furthermore, climate variables significantly impact malaria transmission, yet existing surveillance systems in Ghana do not fully integrate climate data. To address these gaps, a study proposes using climate suitability data to predict the survival rates, distribution, and transmission capacity of malaria vectors across Ghana. By identifying regions where *Anopheles* mosquitoes can thrive and expand, policymakers, including the NMEP, can tailor targeted vector surveillance and control strategies. This approach holds the potential to enhance malaria control, reducing its public health burden in Ghana.

**Keywords:** Climate-based, Modeling, malaria, vector, surveillance, decision-making, Ghana

## 1 INTRODUCTION

Despite efforts to eradicate malaria in sub-Saharan Africa, the African continent still accounts for over 94% of all cases and fatalities worldwide, and no progress has been made since 2017 toward eradication (WHO 2022). The high burden is largely explained by the region's favorable climate for effective malaria parasites

and their vectors to thrive and dominate (Sinka et al. 2010). Anthropogenic climate change adds to the burden, by changing the suitability of landscapes for the proliferation of *Anopheles* mosquitoes (Afrane et al., 2012; Colón-González et al., 2021).

Unfortunately, the current malaria surveillance system in the region is very weak, mainly reliant on healthcare facility-based reporting, which has significant limitations such as underrepresentation of rural areas where healthcare is totally absent or very weak. The surveillance data are typically collected in pieces by different stakeholders and aggregated across the country. Such data are challenging to use to keep track of the disease trends, identify the most afflicted areas or population groups and develop efficient and accessible interventions. Again, malaria transmission is mainly driven by the weather and climate of an area, yet the disease surveillance systems do not operationally use weather and climate impact information to inform intervention. Hence, the absence of a full-scale and robust malaria surveillance and forecasting system is the missing piece of the puzzle that prevents the transition from ad hoc malaria control to elimination in the region. Taking advantage of malaria transmission being climate sensitive and following best practices in weather forecasting, this project seeks to provide real-time malaria surveillance and forecasting information using a more intelligent data-driven surveillance mechanism that is faster, safer, and cheaper. Our idea involves the use of dynamical malaria modeling, incorporating biological, environmental and climatic data, to produce malaria information that can be forecasted, geolocated and mapped in real-time. Our aim is to assist Ghana's National Malaria Elimination Programme (NMEP) achieve its ambitious target of reducing malaria mortality by 100% and cases by 50% by 2028 using the 2022 figures as the baseline. Hence, the model will be operationally run on good computer systems at the Kwame Nkrumah University of Science and Technology (KNUST), Ghana providing forecast information such as malaria case counts, vectorial capacity, extrinsic incubation period, and infectious mosquito bites across Ghana on a spatial scale of 5km and on subseasonal to seasonal time scale. With this real-time surveillance information, the NMCP and other stakeholders involved in malaria decision-making can target malaria control resources such as insecticide treated bed nets, diagnostics and medicines to areas where they are needed most as well as evaluate the impact of malaria control programmes to know which and where it works best. Ultimately, our work will support cost-effective malaria intervention, significantly lower malaria morbidity and mortality and influence better policy making for malaria control in Ghana. Our work will also support the World Health Organization global strategy for malaria control and elimination and contribute to achieving the Sustainable Development Goals (SDGs) such as good health and well-being (SDG3), poverty eradication (SDG1), and reduced inequality (SDG10).

Malaria is an infectious disease, transmitted to humans through the bites of infected female *Anopheles* mosquitoes (Organization et al., 2022). Malaria is life-threatening with a high global burden in sub-Saharan Africa (Organization et al., 2022). According to Organization et al. (2022), about 95% of the global malaria cases and deaths in 2020 occurred in this region, with children under five years of age accounting for 80% of the deaths. Women (especially pregnant women), children and the poorest communities are the most vulnerable to malaria. For instance, malaria affects children's mental and physical development, keeps older children out of school, adults out of work, contributing to the cycle of poverty and negatively impacting the prosperity of individuals and communities. Significant portions of hospital admissions are due to malaria, stressing the already fragile health system. With a stagnation in control since 2017, malaria remains a threat to millions of Ghanaians and sub-Saharan Africans on the whole (Organization et al., 2022).

In sub-Saharan Africa, the impact of climate on malaria vectors and disease transmission has been widely acknowledged. Temperature, rainfall, humidity, land cover change, and vector ecology are key drivers of malaria in both endemic and epidemic areas (Yamba et al., 2023b, 2020). Rainfall, for instance,

provides the environment for vector breeding and relative humidity of at least 60% appears necessary for vector survival (Ermert et al., 2011; Tompkins and Ermert, 2013). Rainfall and relative humidity, therefore, affects the availability, persistence and dimensions of *Anopheles* vectors and their larval habitats (Tompkins and Ermert, 2013; Asare et al., 2016). Temperature, on the other hand, drives the physiological processes of mosquitoes and in the face of temperature change, mosquitoes make necessary physiological adjustments to live either by evolving and adapting to the changes or move to a more suitable area permanently or temporarily (Buckley and Huey, 2016; Villena et al., 2022; Ryan et al., 2023). For instance, the physiological processes of mosquitoes highly fluctuates or constrained by ambient temperature and the rates of the biological and biochemical processes shift with temperature, impacting traits that impact fitness such as development and survival rates (Villena et al., 2022; Abram et al., 2017). Thus temperature contributes to the observed dynamics and distributions of populations of mosquitoes. Anthropogenic climate change adds to the challenge of eliminating malaria by changing the suitability of landscapes for the proliferation of the *Anopheles* mosquitoes (Colón-González et al., 2021). As climate change alters temperatures and weather patterns across the region, the geographic areas where malaria parasites and mosquitoes thrive also changes altering the timings and length of malaria transmission seasons.

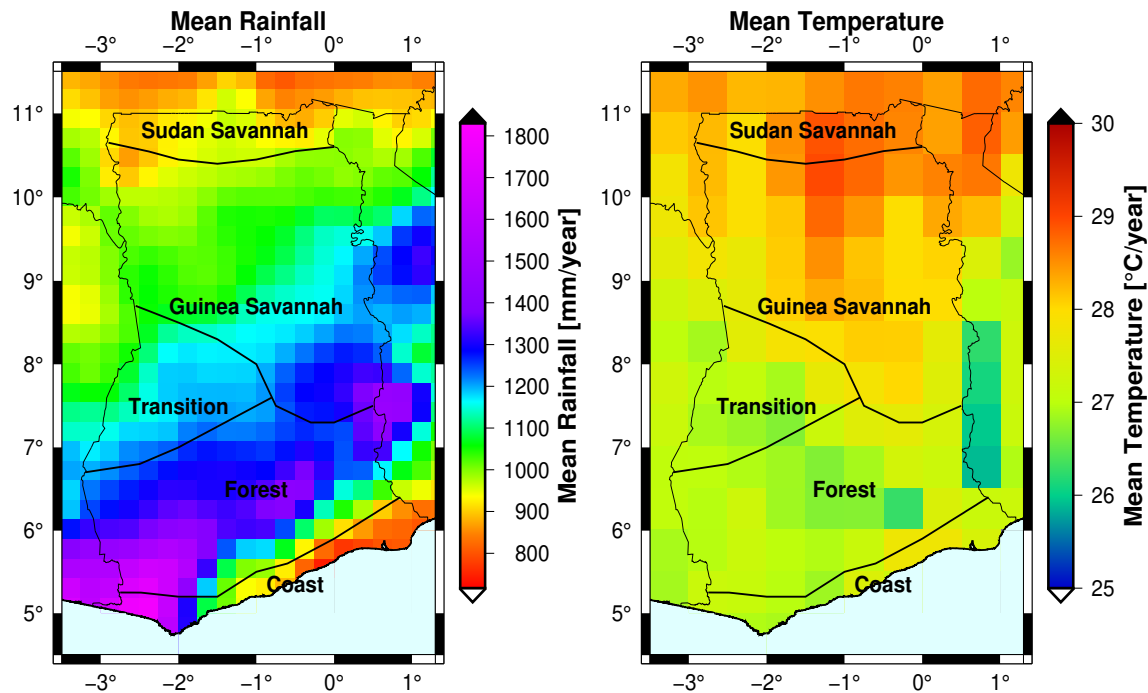
The WHO Global Technical Strategy (GTS) for malaria sets a goal to reduce case incidence and malaria deaths by 90% by the year 2030 referencing 2015 levels. These targets have been missed by 37% and 22% respectively (WHO, 2020) because malaria-determining factors such as climate information, land use/cover change, resistance (parasite, insecticide, drug), accurate diagnosis, and other related environmental factors are not operationally used in African health decision-making processes.

Thus, there is an information gap on the potential impact of climate on malaria vectors thrivability and expansion ranges in Ghana as well as how climate change induces changes in malaria transmission in the country. This gap in information to action cycle is a significant challenge that hinders effective decision-making as far as vector control is concerned. To improve malaria surveillance and support cost-effective malaria intervention strategies we provide the current and future thrivability and expansion range of malaria vectors over Ghana based on climate suitability. Specifically, we used potential climate impact information to predict current and future survival rates, distribution densities and transmission capacity of malaria vectors across Ghana. Using these indices, we ranked spatio-temporally geographic regions where climates proxies provide suitable conditions for the *Anopheles* mosquitoes to thrive and expand. This gives us a clear picture of who is suffering most from the disease and where trends are occurring. With this information, the NMEP and allied policy makers can design targeted vector surveillance and control strategies to eliminate malaria in Ghana. This study holds the potential to significantly enhance malaria control strategies, ultimately reducing the burden of the disease on public health and society at large.

## 2 DATA AND METHODS

### 2.1 Study area

Ghana is a West African country situated between latitudes 4.5°N and 11.5°N and longitude 3.5°W and 1.5°E (see Fig 1). The country has a tropical monsoon climate governed by the West African Monsoon (WAM) (Ansah et al., 2020; Aryee et al., 2018). The monsoon climate is further categorized into five distinct agro-climatic zones namely Sudan Savannah, Guinea Savannah, Transition, Forest and Coastal zones (Yamba et al., 2023a). Each zone has a distinct climate features from others and hence influence malaria transmission differently (Yamba et al., 2023b). The northern Ghana, that encompasses the Sudan



**Figure 1.** The map of Ghana showing the agro-climatic zones as well as spatial distribution of annual total rainfall and temperature. Source: (Yamba et al., 2023a)

and Guinea savannah, is characterized by uni-modal rainfall distribution which starts from April through mid-October with peak rainfall in August or September (Yamba et al., 2023a). The southern Ghana, encompassing the Transition, forest, and coastal zones has a bi-modal rainfall distribution. The first season runs from March to July, with peak in June, while the second season runs from September to mid-November, with peak in October (Yamba et al., 2023a). Between December and February, the harmattan, a north-easterly desert wind, dominates the country. The harmattan winds are more prevalent in the north, lowering humidity and resulting in hotter days and cooler nights in this area of the country (Aryee et al., 2018).

## 2.2 Data

### Rainfall

Daily rainfall data spanning the period 1991 – 2020 was extracted from the Climate Hazards Group Infra-Red Precipitation (CHIRPs) (Funk et al., 2015) and used in this study. CHIRPS is a gridded satellite-gauge product with a high spatial resolution of  $0.25^\circ$  by  $0.25^\circ$  and available globally on a daily time scale from 1981 to the present. CHIRPS was chosen because it is built from a combination of satellite and quality-controlled in situ data from ground-based weather stations. Moreover, previous studies (Gleixner et al., 2020; Parsons et al., 2022; Verdin et al., 2020) have validated the products and found it to have very good correlation with ground-based observations and lower biases across Africa.

### Temperature

Similarly, daily 2m temperature data covering the years 1991–2020 were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis, 5th generation (ERA5) (Hersbach et al., 2020) for this study. ERA5 is a gridded re-analysis product with a high spatial resolution of  $0.25^\circ$  by  $0.25^\circ$  and available globally on an hourly time scale from 1979 to the present. ERA5 was preferred to

other temperature products because of its high temporal availability (hourly from 1979 to present) and high spatial resolution (0.25° by 0.25°). Besides, validation studies (Gleixner et al., 2020; Parsons et al., 2022) have widely recommended it for meteorological research across Africa.

### Predicted rainfall and temperature

For future analysis, daily rainfall and temperature data spanning the period 2031 – 2090 was extracted from the Coordinated Regional Climate Downscaling Experiment (CORDEX) simulation framework database. The CORDEX experiments consist of a different combinations of Global Climate Models (GCMs) and Regional Climate Model (RCM) simulations for different future climate scenarios (forcings) namely RCP2.6 RCP4.5 and RCP8.5 as well as different ensemble members of the same GCM-RCM combinations. Rainfall and temperature output from Regional Model version 2015 (REMO2015) driven by MPI-ESM-LR was extracted and used in this work. The rainfall data is available for the Africa Domain at horizontal grid spacing of 0.22° by 0.22° spanning the period 1950 to 2100. We temporally validated different CORDEX model data against observations over Ghana and found good performance from the MPI-ESM-LR. Again, previous validation studies (Ilori and Balogun, 2021) have found a good performance of the models in replicating rainfall and temperature over Africa.

## 2.3 Analysis

We analyzed the impact of climate on the capacity of anopheles mosquitoes to thrive and transmit malaria using the Vectorial Capacity (VC) index. VC is defined as the rate at which mosquitoes can transmit parasites to humans (Shapiro et al., 2017). VC depends on a number of entomological factors involved in malaria transmission cycle namely vector density in relation to man ( $m$ ), survival rate of malaria vectors ( $P$ ), man-biting frequency ( $a$ ), length of the sporogonic cycle expressed as Extrinsic Incubation Period (EIP), proportion of anopheline vectors with sporozoites that are actually infective ( $b$ ) and human-to-mosquito transmission efficiency ( $c$ ). The combined effect of these factors is expressed mathematically (Paaijmans et al., 2012) as:

$$VC = \frac{ma^2bcP^{EIP}}{-\ln(P)} \quad (1)$$

The survival rate of malaria vectors,  $P$ , is a function of temperature and expressed mathematically using Martens II temperature scheme (Ermert et al., 2011; Lunde et al., 2013) as follows:

$$p_i = \exp\left(\frac{-1}{-4.4 + 1.31T_i - 0.03T_i^2}\right) \quad (2)$$

where  $T_i$  represents the air temperature the mosquitoes experience on daily basis. Similarly, the Extrinsic Incubation Period (EIP) is also a function of temperature and was calculated using the formulation proposed by (Detinova et al., 1962):

$$EIP = \frac{D_s}{T_i - T_s} \quad (3)$$

where  $D_s$  represent the sporogonic cycle length in degree days,  $T_s$  is the sporogonic temperature threshold and  $T_i$  is the temperature experienced by mosquitoes on daily basis. The vector biting frequency ( $a$ ) was adapted from Ceccato et al. (2012) and calculated using the equation:

$$a_i = \frac{HBI}{(1 + \frac{D_g}{T_i - T_g})}$$
 (4)

where HBI is the human Blood Index,  $T_g$  is the minimum temperature for the gonotrophic cycle and  $D_g$  is the gonotrophic cycle length in degree days.

Temperature drives the physiological processes of mosquitoes and in the face of temperature change, mosquitoes make necessary physiological adjustments to live either by evolving and adapting to the changes or move to a more suitable area permanently or temporarily (Buckley and Huey, 2016; Villena et al., 2022; Ryan et al., 2023). Thus, the rate of the biological and biochemical processes of mosquitoes shift with temperature, impacting on mosquito traits such as development, biting rates (a), EIP and survival rates (Villena et al., 2022; Abram et al., 2017) as expressed in eqns 4, 3 and 2.

Rainfall (RR) on the other hand, provides the environment for vector breeding and relative humidity of at least 60% appears necessary for vector survival (Ermert et al., 2011; Tompkins and Ermert, 2013). Rainfall therefore, affects the availability, persistence and dimensions of Anopheles vectors and their larval habitats (Tompkins and Ermert, 2013; Asare et al., 2016). This impact is expressed as having a direct link with the vector density in relation to man (m) with Eqn 1 being re-expressed as:

$$VC = \frac{(RR * m)a^2bcP^{EIP}}{-In(P)}$$
 (5)

where RR is the daily rainfall.

Details of the parameter constants and the literature references from which they were obtained are shown in Table 1.

**Table 1.** Default values of the climate-independent malaria model parameters.

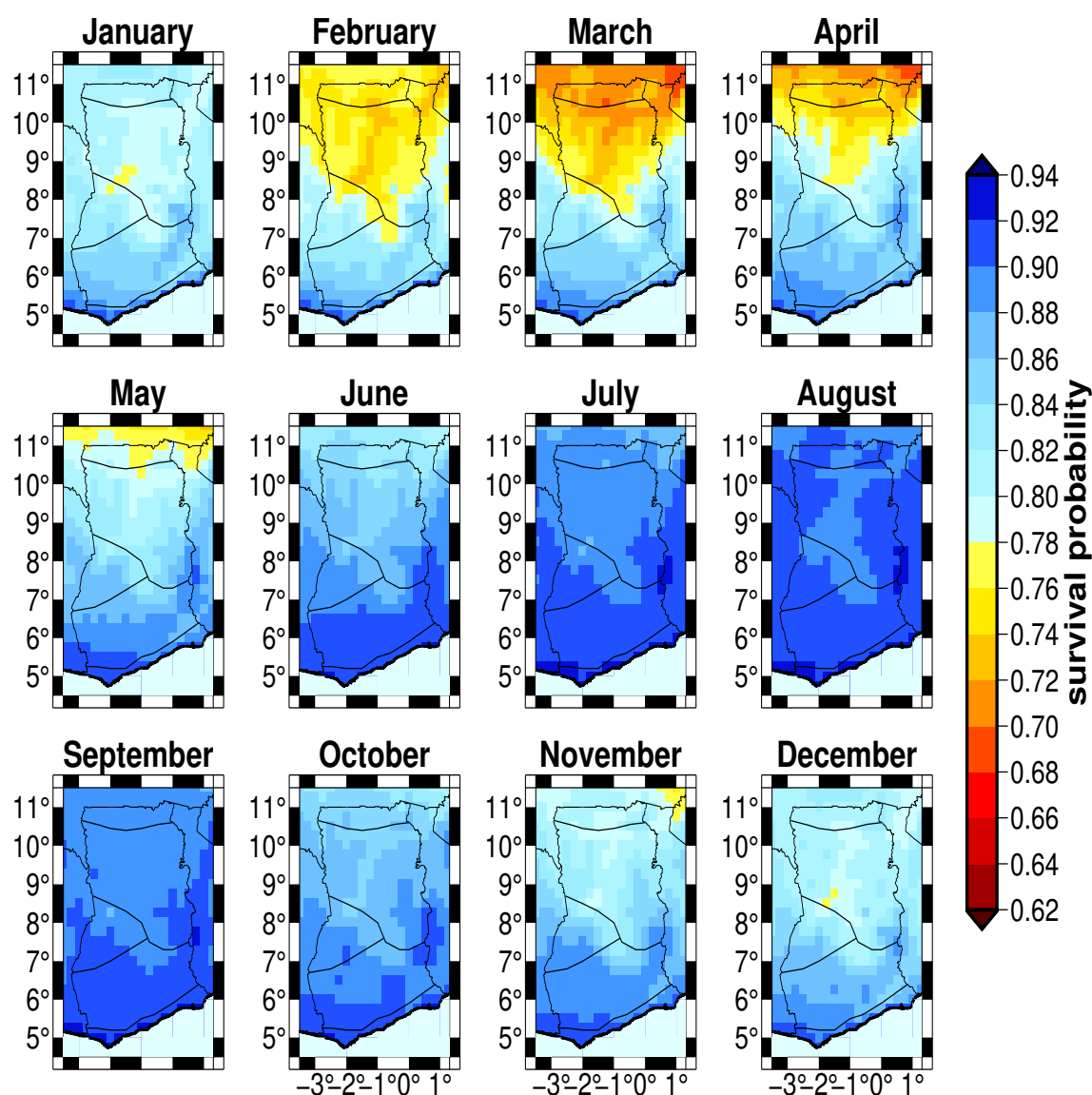
| Parameter                                       | Symbol               | Value     | Reference   |
|---|----------------------|-----------|---|
| Human Blood Index                               | <i>HBI</i>           | 0.8       | (Ermert et al., 2011)   |
| Minimum temperature for gonotrophic cycle       | <i>T<sub>g</sub></i> | 7.7 °C    | (Detinova et al., 1962; Ermert et al., 2011; Tompkins and Ermert, 2013) |
| Gonotrophic cycle length in degree days         | <i>D<sub>g</sub></i> | 37.1      | (Detinova et al., 1962; Ermert et al., 2011; Tompkins and Ermert, 2013) |
| Minimum temperature for sporogonic cycle        | <i>T<sub>s</sub></i> | 16 °C     | (Ermert et al., 2011; Tompkins and Ermert, 2013)                        |
| Sporogonic cycle length in degree days          | <i>D<sub>s</sub></i> | 111.0     | (Detinova et al., 1962; Ermert et al., 2011; Tompkins and Ermert, 2013) |
| Mosquito-to-human transmission efficiency       | <i>b</i>             | 0.3       | (Ermert et al., 2011; Tompkins and Ermert, 2013)                        |
| Human-to-mosquito transmission efficiency       | <i>c</i>             | 0.2       | (Ermert et al., 2011; Tompkins and Ermert, 2013)                        |
| Vector: Human ratio                             | <i>m</i>             | 4         | (Ermert et al., 2011; Tompkins and Ermert, 2013)                        |
| Probability that a vector feeds on a human host | <i>a</i>             | see Eqn 4 | (Ceccato et al., 2012)  |

The VC was then calculated using Eqn ?? with inputs from eqns 2, 3, 4 and information in Table 1. Using the outcome, we mapped out areas of suitable climate conditions for anopheles vectors to thrive and transmit malaria for enhance vector surveillance and control across Ghana.

3 RESULTS

Figure 2 illustrates the monthly survival rates of malaria vectors, offering valuable insights into their regional variations. It can be seen that, the northern regions of the country exhibit the lowest survival rates during the months of February, March, April, and May, ranging from 0.6 to 0.8. Among these months, May

185 stands out with a relatively higher survival rate, while March records the lowest survival rate in this period.  
186 Moving towards the southern regions, we observe a noticeable increase in survival rates, ranging from 0.78  
187 to 0.8, with peaks observed in the extreme southwest. The months of November, December, and January  
188 follow a similar spatial pattern, but with an overall higher rate of survival compared to February, March,  
189 and April. During this period, survival rates range from 0.78 to 0.84, with the highest rates concentrated in  
190 the southwestern part of the country, reaching a peak of 0.84. June and October had similar characteristics,  
191 a relatively higher rates of vector survival than the mentioned months with rates ranging from 0.86 in  
192 the northern regions to 0.9 in the southern regions. Remarkably, the survival rates in July, August, and  
193 September are consistently the highest nationwide, peaking at an impressive 0.94. This finding underscores  
194 the significance of these months in terms of malaria vector survival and highlights the need for targeted  
195 interventions during this period. These findings provide valuable insights into the geographic and temporal  
variations in malaria vector survival rates.



**Figure 2.** The spatial patterns of vector survival probabilities on monthly time scale

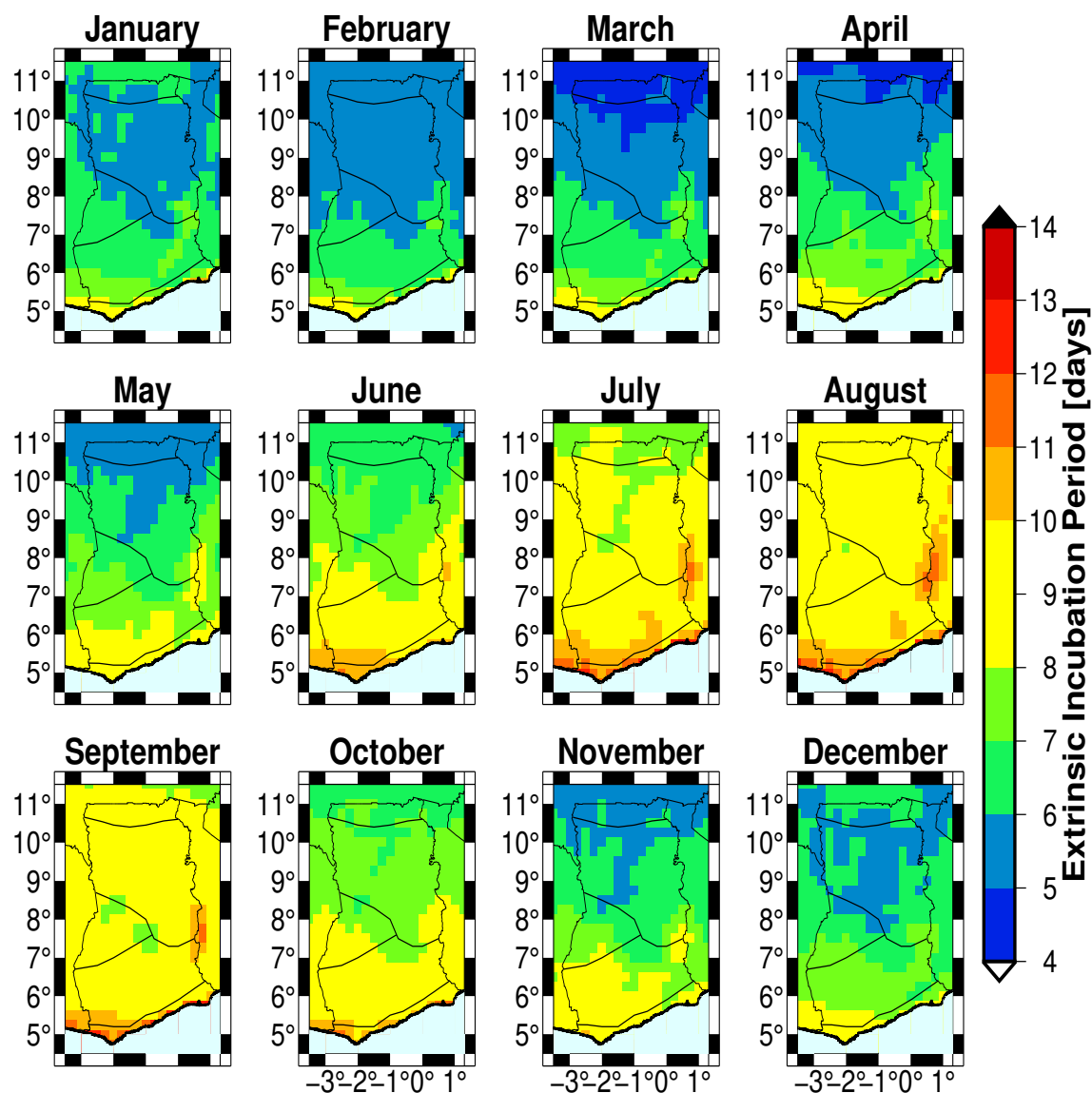


197 In figure 3, we present our findings regarding the duration required for parasite development within  
198 mosquitoes across different months of the year. We observe that in the Northern regions of the country,  
199 during the months of February, March, and April, the parasite development within mosquitoes takes a  
200 relatively shorter period, ranging from 5 to 6 days. In contrast, the Southern regions exhibit a longer  
201 duration, with parasite development requiring 6 to 8 days during the same months. Transitioning into  
202 the months of November, December, January, and May, we note an increase in the duration required  
203 for parasite development, although this increase is not as significant when compared to the remaining  
204 months (June, July, August, September, and October). In the Northern regions, the transition period extends  
205 from 6 to 7 days, while in the Southern regions, it ranges from 7 to 9 days. The months of June and  
206 October display intermediate values, with parasite development taking 7 to 8 days in the Northern regions  
207 and 8 to 10 days in the Southern regions. July, August, and September present the longest duration for  
208 parasite development, ranging from 8 to 12 days. Among these three months, July and September observe  
209 the shortest development period in the Northern part of the country in July and in the transition belt in  
210 September, with both registering 8 days. In contrast, August stands out as the month with the lengthiest  
211 development period throughout the entire country, spanning from 10 to 12 days, with peaks observed in the  
212 extreme south and the central regions along the Ghana-Togo border.

213 Considering three distinct climate periods, we sought to estimate the average duration of malaria  
214 transmission in a typical year. Figure4 provides a visual representation of the total number of months during  
215 which malaria transmission occurs in the current climate period (1991-2020), as well as projections for the  
216 near and far future. During the current climate period, malaria transmission is predominantly concentrated  
217 in the southern regions of the country, where it occurs year-round. Notably, the Coastal regions stand out  
218 as areas with continuous transmission throughout the entire year. Following closely are the forest zones,  
219 where malaria transmission is observed for 11 to 12 months annually. The transition regions exhibit a  
220 similar pattern, with a total of 10 to 12 months of malaria transmission within a year. Subsequently, the  
221 northern region of the country experiences a relatively lower duration of malaria transmission. Specifically,  
222 in the Savannah zone, there are 8 to 9 months of malaria transmission in a typical year, while in the Sudan  
223 Savannah, the transmission period spans from 6 to 8 months. Looking ahead to the near future (2031-2060),  
224 our projections indicate potential changes in the spatial distribution and the duration of malaria transmission  
225 across different regions of Ghana. In the southern region, there is an expected decrease in the number of  
226 months of malaria transmission. Specifically, the Coastal zones are projected to experience transmission  
227 for 11 months, while the Forest zones may see transmission for 10 to 11 months. The transition zones are  
228 also expected to exhibit a reduction in transmission, with periods ranging from 8 to 10 months. Conversely,  
229 the northern regions are anticipated to witness an increase in the duration of malaria transmission. In the  
230 Savannah zones, the transmission period is expected to extend from 8 to 9 months to 8 to 11 months.  
231 Similarly, in the Sudan Savannah, the transmission period is projected to increase from 6 to 8 months  
232 to 7 to 9 months. Looking further into the far future (2061-2090), the duration of malaria transmission  
233 remains relatively stable in the southern regions, ranging from 8 to 11 months. However, there is a notable  
234 shift in the spatial distribution within the region. Specifically, significant portions of the Forest zones are  
235 expected to experience an increase in transmission duration, now totaling 9 months. This change suggests a  
236 potential expansion of malaria transmission into areas that previously had a shorter transmission season  
237 within the southern region. The northern regions, particularly the Sudan Savannah, are projected to see  
238 a further increase in the duration of malaria transmission. The transmission period is expected to extend  
239 from 6 to 8 months to 8 to 9 months in this region.

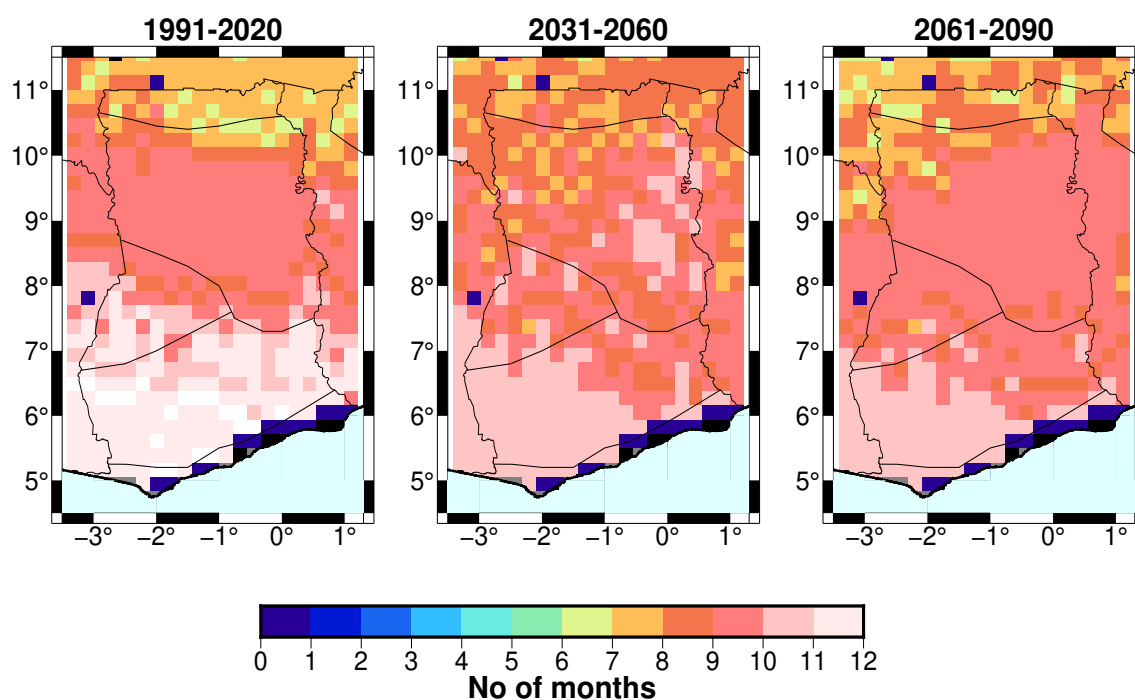
240 In Figures 5 and 6, we present our assessment of the averaged monthly spatial distributions of mosquito  
241 densities across the country, spanning the period from 1991-2020 and projecting into 2031-2060. Figure 5





**Figure 3.** The spatial patterns of EIP on monthly time scale

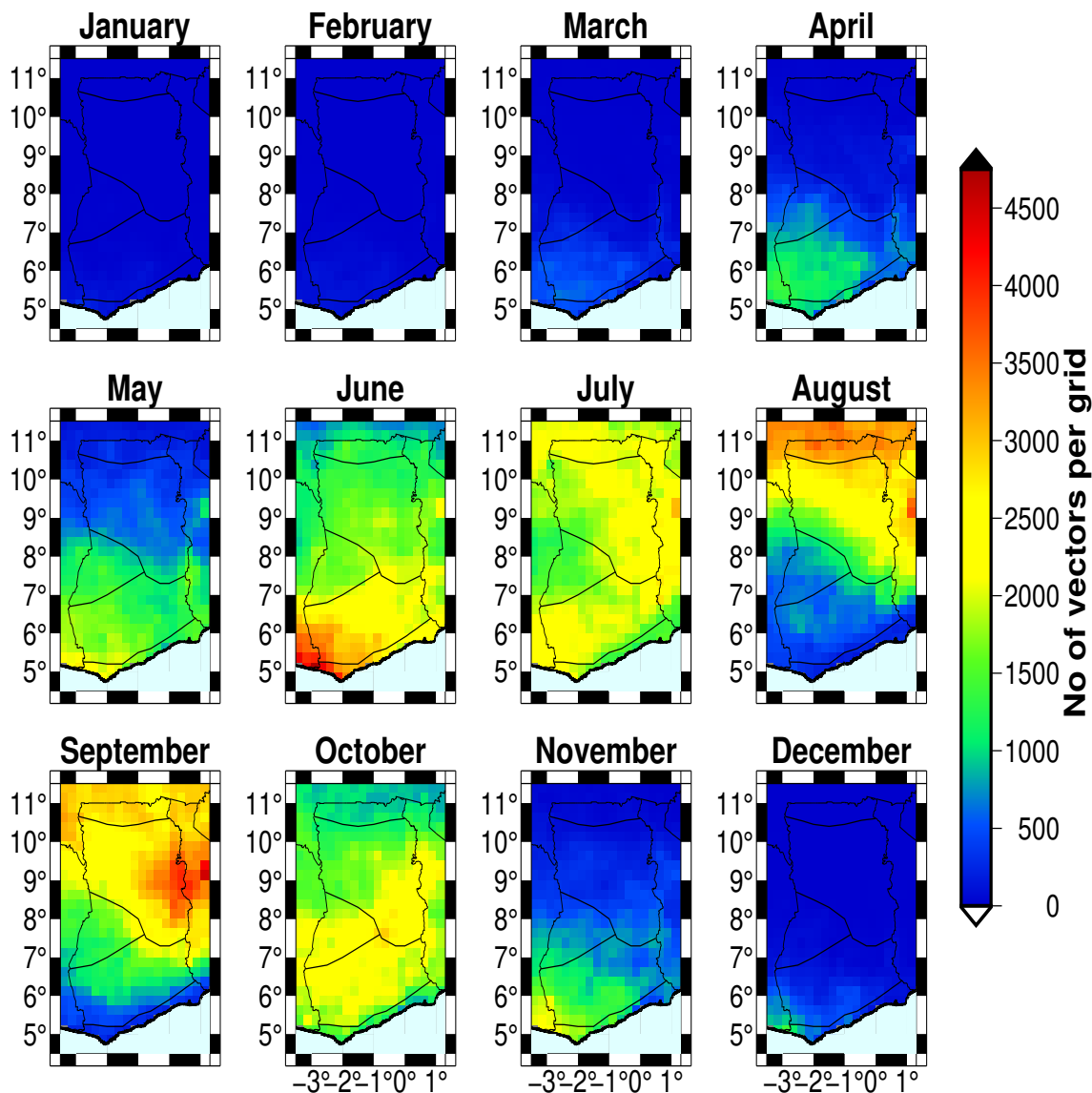
242 highlights the most populated months across the entire country during the reference period (1991-2020).  
243 June, July, and October stand out as the months with the highest mosquito densities, with populations  
244 ranging from 2000 to 3500 mosquitoes per 24.42  $km^2$ . August and September, on the other hand, record  
245 the highest number of vectors in the northern regions of the country, surpassing 3500 mosquitoes per 24.42  
246  $km^2$ . August witnesses this high density in the Sudan Savannah, while September experiences it in the  
247 Akuampem Mampong ranges within the transition zones. Conversely, during the months of December,  
248 January, February, and March, the country as a whole records the lowest number of mosquito vectors, with  
249 densities falling below 500 mosquitoes per 24.42  $km^2$ . The remaining months, April, May, and November,  
250 exhibit similar characteristics, with relatively higher mosquito populations in the southern regions, although  
251 these populations are still lower compared to the peak months of June, July, and October. Projecting into  
252 the future (2031-2060), mosquito densities are expected to increase substantially to alarming levels during  
253 the months of August, September, and October, primarily in the Northern regions. These months will  
254 witness a surge in mosquito populations, which is a cause for concern. The mosquito densities during this



**Figure 4.** Malaria transmission months

period are projected to surpass historical records, posing potential challenges for malaria control efforts in these regions. Conversely, the months known for lower mosquito densities (December, January, February, and March) are anticipated to maintain their levels, with no significant deviations from historical patterns. However, there is some positive news in the projections as well. Densities in the months of April, May, and November are expected to experience slight reductions, particularly in the southern regions. While these months typically exhibit higher mosquito populations in the south, the projected decreases suggest a potential improvement in the mosquito situation during these periods.

In figure 7, we present an analysis of the average number of infectious bites received in a month from 1991-2020. Within the twelve months, the highest number of infectious bites was observed in October, around the south-eastern parts of the guinea Savannah, followed by September in the Sudan and north eastern regions of the guinea Savannah. August, July and June follows in a chronological order, with 70,60 and 50 maximum of infectious bite rate respectively. Throughout the country the months of December, January, February, March and April receives relatively low values of EIR in a typical year. Among the twelve months examined, October emerges as the month with the highest number of infectious bites. This peak in infectious bite rates is primarily concentrated in the southeastern parts of the Guinea Savannah region. Following closely, September records the second-highest number of infectious bites, particularly in the Sudan and northeastern regions of the Guinea Savannah. August, July, and June sequentially follow with decreasing maximum infectious bite rates of 70, 60, and 50, respectively. These months collectively represent a period of heightened malaria transmission risk in various regions of the country. In contrast, the months of December, January, February, March, and April receive relatively low values of Entomological Inoculation Rate (EIR) in a typical year. During these months, the risk of infectious mosquito bites is comparatively lower nationwide. Looking ahead into the future (2031-2060) as can be seen in figure 8, our projections indicate significant changes in the spatial and temporal distribution of the number of infectious mosquito bites received in a square kilometer. We anticipate notable shifts in the dynamics of

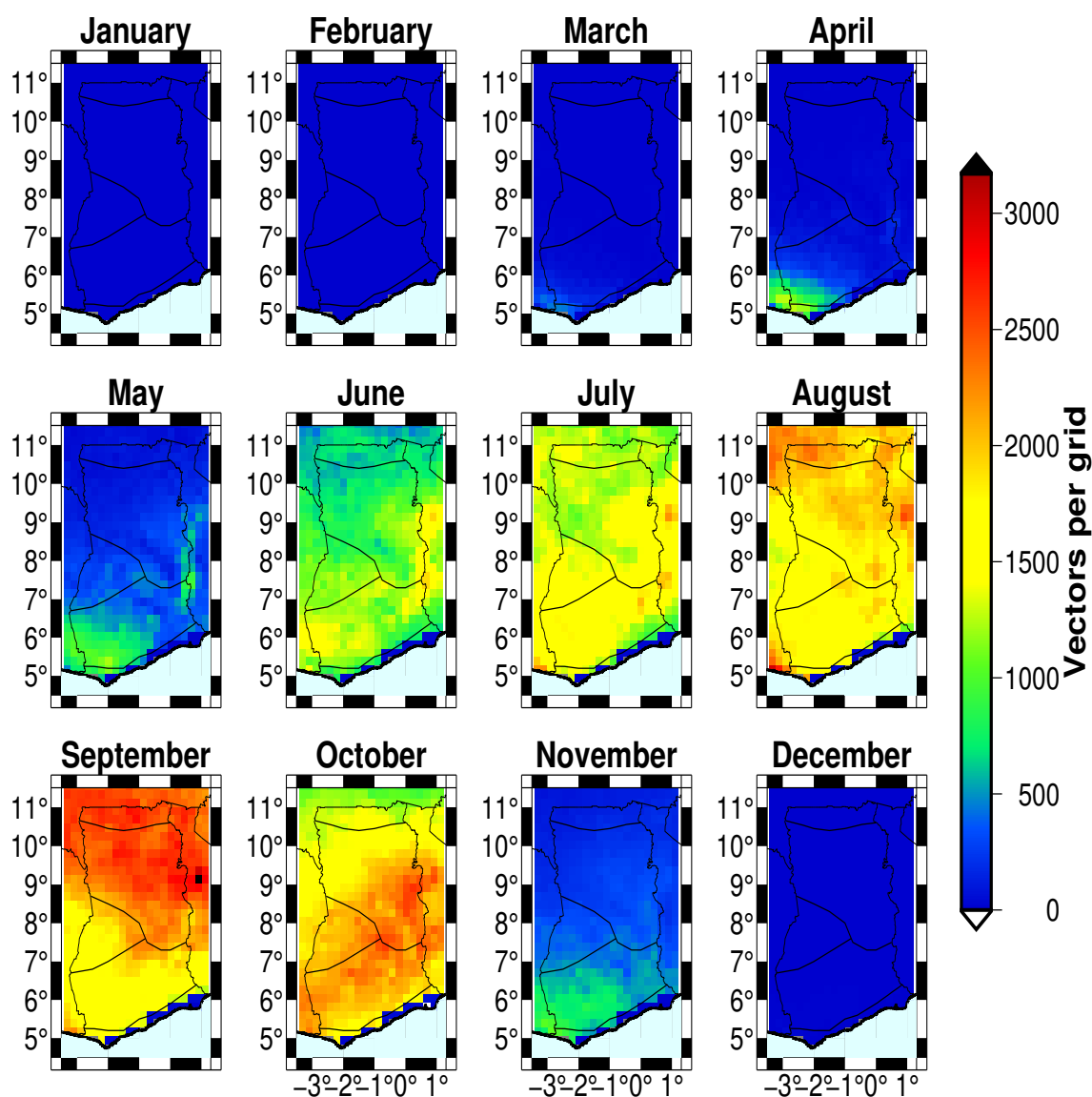


**Figure 5.** Vector distribution density from 1991-2020

infectious bites. September and October are expected to experience a substantial increase in infectious bites, particularly in the northern regions of the country. On the positive side, the remaining months are expected to maintain a relatively stable EIR nationwide. This stability suggests that the risk of infectious mosquito bites during these months will not undergo significant changes compared to historical patterns.

4 DISCUSSION

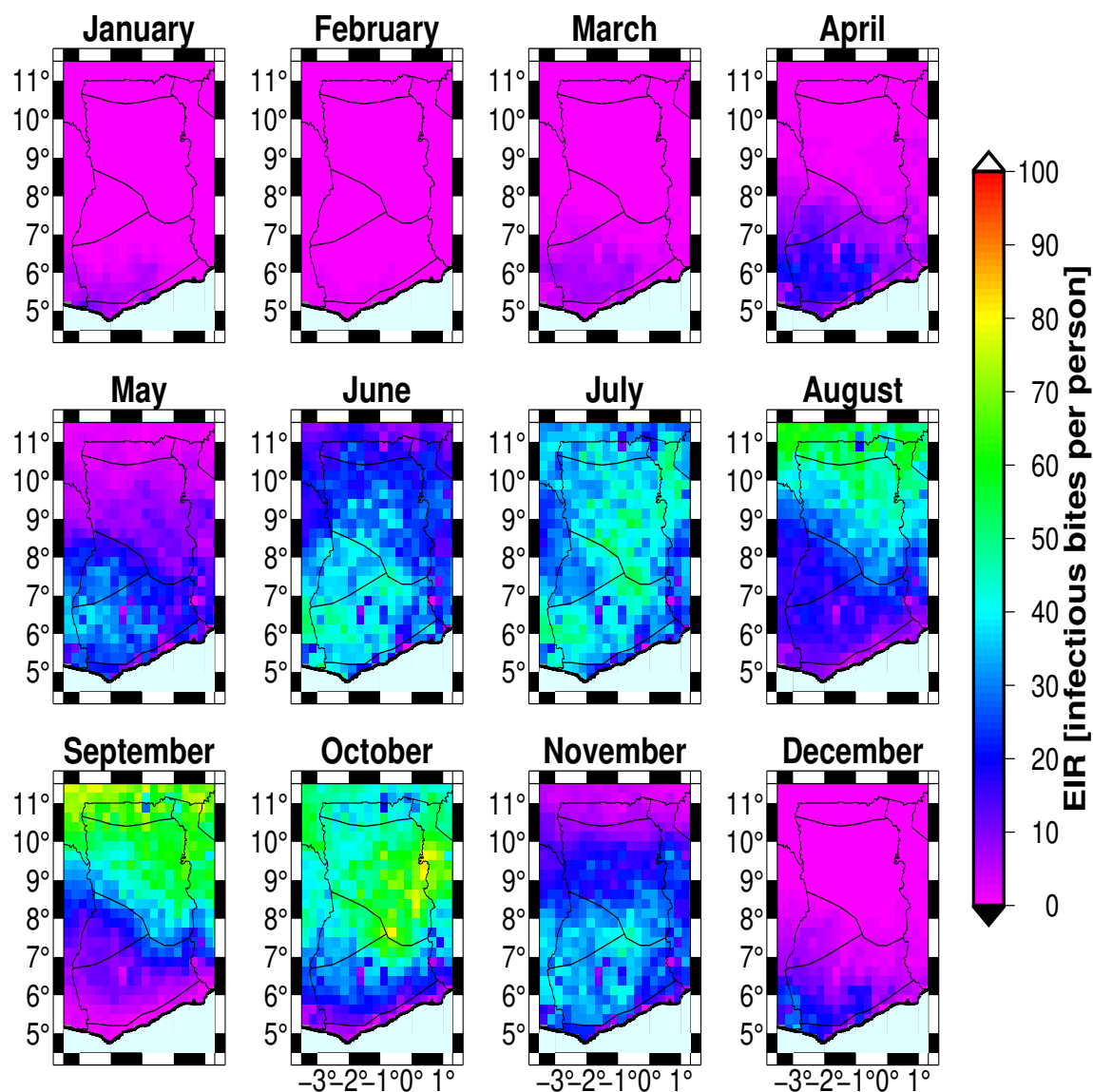
In this study, we developed a climate based malaria modelling framework to enhance malaria vector surveillance and inform decision-making strategies in Ghana by uncovering a nuanced picture of the spatial and temporal variations in the key factors influencing malaria risk. Our analysis unequivocally demonstrates that malaria vectors exhibit a higher susceptibility to thrive in the southern regions of Ghana, a finding that aligns seamlessly with the assessment conducted by (Hinne et al., 2021) on the distribution of malaria vectors across distinct ecological zones within Ghana. Delving deeper into the geographical disparities, we observe a remarkable decline in the risk of vectors thriving during typical dry months in the northern



**Figure 6.** Vector distribution density 2031-2060

290 region. The rationale behind this decline lies in the apparent scarcity of suitable breeding grounds for  
 291 mosquitoes in these sectors, leading to a notable reduction in their populations. This starkly contrasts with  
 292 the situation in the southern region, where even during the dry season, the occasional rainfall bestows a  
 293 significantly higher probability for mosquito survival. Temperature and humidity play crucial roles in this  
 294 phenomenon as well. As one moves northward in Ghana, temperatures tend to rise, with occasional spikes  
 295 of up to  $40^{\circ}\text{C}$ . Mosquitoes, known for their ability to withstand colder temperatures (less than  $40^{\circ}\text{C}$ ),  
 296 find the more favorable conditions in the south, resulting in a diminished mosquito population during  
 297 the specified months, as depicted in Figure 5. Further narrowing our focus to the months spanning from  
 298 November to March, we unveil a consistent trend of low mosquito presence throughout the country. The  
 299 prevailing weather conditions during this period are not conducive to the proliferation of malaria, leading  
 300 to a reduced mosquito population and subsequently fewer instances of biting and infectious bites. The  
 301 empirical evidence supporting this trend is underscored in Figure 7.

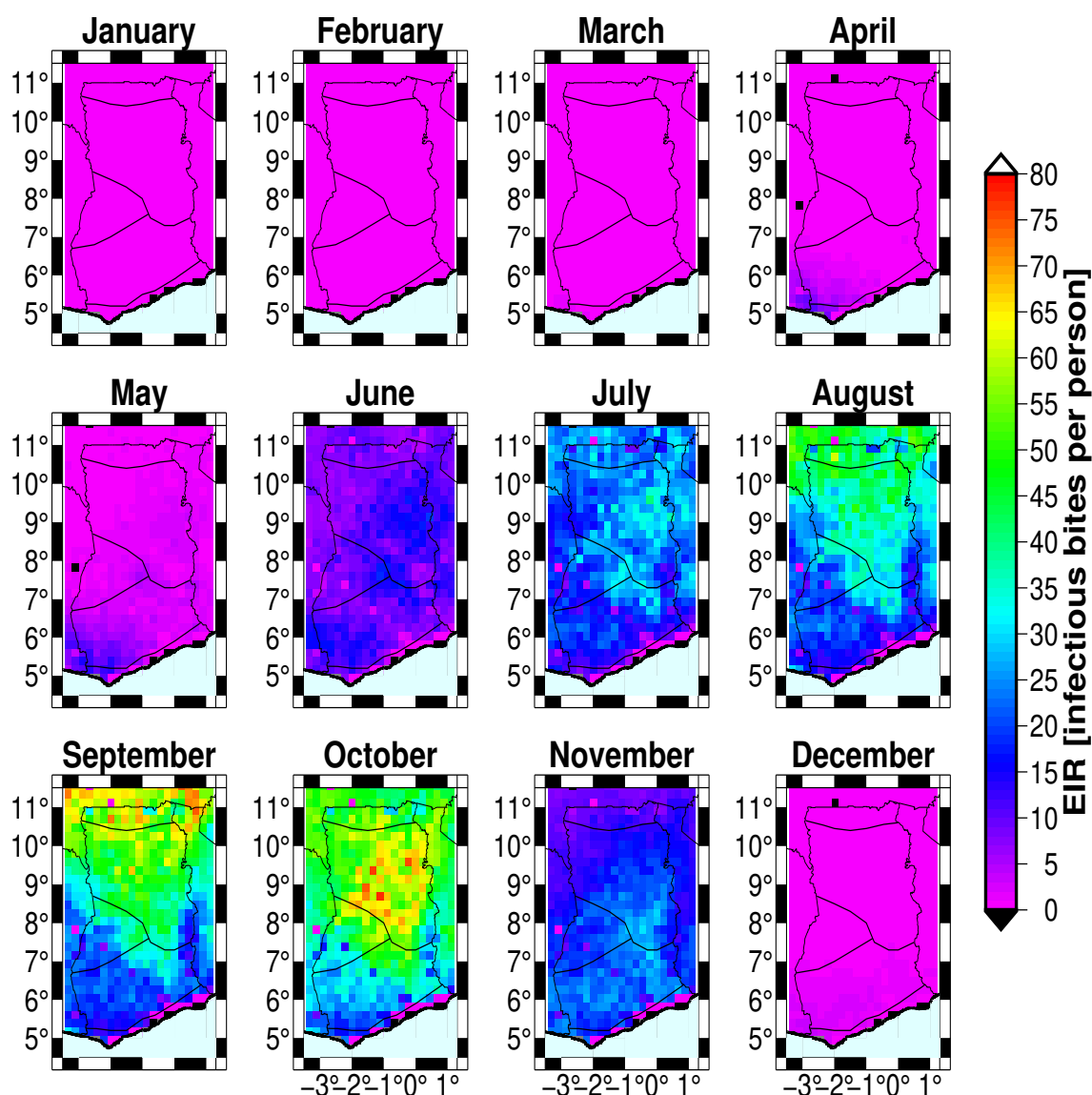
302 These findings enable the identification of high-risk areas and critical timeframes for malaria transmission.



**Figure 7.** Spatio-temporal distribution of EIR from 1991-2020

303 These projections highlight the dynamic nature of malaria transmission and the need for adaptive strategies  
304 to address changing patterns. It is essential to closely monitor these developments and adjust malaria  
305 control efforts accordingly, with a focus on both maintaining progress in areas with decreasing transmission  
306 and implementing targeted interventions to mitigate the spread of malaria in regions experiencing extended  
307 transmission seasons.

308 Additionally, the data we have produced can guide the design of vector control strategies tailored to  
309 specific regions and seasons. The projections for the future also serve as an early warning system, alerting  
310 health authorities to potential shifts in transmission dynamics. This allows for proactive planning and rapid  
311 response, helping to prevent outbreaks and reduce the overall malaria burden.



**Figure 8.** Spatio-temporal distribution of EIR from 2031-2060

## 5 CONCLUSION

312 This research aims to contribute to the understanding of the intricate relationship between climate and  
 313 malaria transmission in Ghana. The outcomes of this study will include:

314 Climate-based Model: A robust predictive model that accurately forecasts the distribution and abundance  
 315 of malaria vectors based on climate conditions.

316 Insights into Climate-Vector-Disease Nexus: A better understanding of how climate influences vector  
 317 population dynamics and disease transmission, allowing for more targeted interventions.

318 Climate Change Impact Assessment: Insights into the potential impact of climate change on malaria  
 319 transmission, enabling proactive adaptation strategies.

320 Policy Recommendations: Actionable recommendations for public health authorities to optimize vector  
 321 surveillance and control efforts based on climate-driven predictions.

## 6 ADDITIONAL REQUIREMENTS

For additional requirements for specific article types and further information please refer to Author Guidelines.

## CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## AUTHOR CONTRIBUTIONS

The Author Contributions section is mandatory for all articles, including articles by sole authors. If an appropriate statement is not provided on submission, a standard one will be inserted during the production process. The Author Contributions statement must describe the contributions of individual authors referred to by their initials and, in doing so, all authors agree to be accountable for the content of the work. Please see here for full authorship criteria.

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## SUPPLEMENTAL DATA

Supplementary Material should be uploaded separately on submission, if there are Supplementary Figures, please include the caption in the same file as the figure. LaTeX Supplementary Material templates can be found in the Frontiers LaTeX folder.

## DATA AVAILABILITY STATEMENT

The Climate Hazards Infra-Red Precipitation (CHIRPs) database can be found in the Climate Hazard Center repository at <https://www.chc.ucsb.edu/data/chirps>. The 2m temperature data from the European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis, 5th generation (ERA5) is available at the copernicus data repository under the link: <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form>. The Coordinated Regional Climate Downscaling Experiment (CORDEX) simulation framework database is available at the CORDEX data repository at <https://cordex.org/data-access/cordex-data-on-esgf/>



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## FIGURE CAPTIONS



**Figure 9.** Enter the caption for your figure here. Repeat as necessary for each of your figures



**Figure 2a.** This is Subfigure 1.



**Figure 2b.** This is Subfigure 2.

**Figure 2.** Enter the caption for your subfigure here. **(A)** This is the caption for Subfigure 1. **(B)** This is the caption for Subfigure 2.