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Abstract

Efforts towards malaria control in Ghana have had positive impacts. However, these efforts need to be locally tailored to further accelerate progress. The aim of this study was to examine the climatic drivers of malaria transmission in the Greater Accra Region and identify inter-district variation of malaria burden. Monthly malaria cases for the Greater Accra Region were obtained from the Ghanaian District Health Information and Management System. Malaria cases were decomposed using the seasonal-trend decomposition, based on locally weighted regression to analyse the seasonality. A Poisson regression model with a conditional autoregressive prior structure was used to quantify associations between climatic variables and malaria risk, and spatial dependence. Posterior parameters were estimated using Bayesian Markov chain Monte Carlo simulation with Gibbs sampling. A total of 1,105,370 malaria cases was recorded in the region from 2015–2019. The overall malaria incidence rate for the region was approximately 1 per 1,000,000 population. Malaria transmission was highly seasonal with an irregular inter-annual pattern. Malaria incidence was found to increase by 0.1% (95% credible interval [CrI]: 0.02–0.16%) for a 1°C rise in monthly maximum temperature lagged at 6 months and 0.2% (95% CrI: 0.5–0.3%) for 1°C rise in monthly minimum temperature without lag. No spatial dependency was observed after accounting for climatic variables. Only five districts located in the south-central part of the region had a malaria incidence rate that was lower than the regional average at >95% probability level. The distribution of malaria cases was heterogeneous, seasonal and significantly associated with climatic variables. Targeted malaria control and prevention in high-risk districts at the appropriate time points could result in a significant reduction in malaria transmission in the Greater Accra Region.

Background

Malaria is a preventable and treatable parasitic infectious disease transmitted by the female Anopheles mosquito. In 2019, an estimated 229 million new malaria cases, and 409,000 malaria deaths occurred globally [1]. However, this burden is not distributed evenly. It is estimated that around 93% of malaria cases occur in the World Health Organization (WHO) African Region. Also, the most vulnerable group affected by malaria are children under five-years of age, accounting for 67% of the total malaria mortality burden [1]. Malaria transmission is affected by multidimensional factors, linked to vector characteristics, climatic conditions, land cover, genetics and human behaviour [2]. These disparate factors mean that malaria transmission rates can vary significantly at local levels.

Malaria is a major cause of morbidity, and the leading cause of mortality in Ghana [3]. The country experienced half a million new cases of malaria in 2018, or 3% of all global malaria cases and around 11,000 deaths [4]. The total number of active malaria cases is currently around 6.6 million, from a population of 29 million people.

WHO guidelines for malaria control incorporate vector control measures using insecticide treated nets (ITNs) and indoor residual spraying (IRS), prompt diagnosis, and treatment. These control measures are further supported by implementation of the intermittent preventive therapy protocol (IPTp) in pregnant women [4, 5]. In Ghana, the adoption of these approaches, together with increased health promotion and educational campaigns has led to significant reductions in malaria incidence and mortality [6]. Malaria-associated mortality has been reduced by 14.8% in 2016 compared to 2010 [7]. Case fatality rates in children below the age of 5 years experienced a 4% reduction within the same timeframe. In addition, the facility-based malaria fatality rate for children aged under five years reduced from 14% in 2000 to 0.5% in 2016 [3]. Despite these achievements, malaria remains a major health burden, and the reductions in incidence and mortality may not be sustained. In fact, there was an 8% increase in malaria cases in Ghana in 2018 compared to 2017 [4].

Although the national prevalence of malaria is estimated to be high, there is variability in terms of location, seasonality and social and economic sectors [8, 9]. Malaria prevalence tends to be higher in rural localities than in urban areas. The Greater Accra Region had the lowest prevalence malaria (5%) among children aged under 5 years in the country in 2016, in contrast to the Northern region (25%) and Eastern and Central regions (both with 31%) [9]. This heterogeneity is influenced by several factors such as the immune profile of populations, stability of mosquito breeding places (relating to climate factors), varying density of populations and accessibility to public health interventions and healthcare [10, 11]. Despite all these findings, policies on malaria prevention and control are mostly designed based on national-level aggregated data, which may not be a true reflection of disease distribution at the regional and local levels.

Few studies have utilised spatial and temporal analysis to characterise patterns of malaria risk or identify environmental factors associated with the malaria distribution in Ghana. This study aimed at assessing the climatic drivers of malaria in the Greater Accra Region (Fig. 1) and identifying inter-district variation of malaria burden. The goal was to inform the development of focused interventions for malaria control by program officials in Ghana.

Results

Descriptive analysis

A total of 1,105,370 malaria cases were recorded in the region during the study period (2010–2019). The overall malaria incidence was approximately 1 per 1,000,000 population. Malaria transmission was spatially heterogeneous across the study area (Fig. 2), but all districts recorded cases during the study period. Ashaiman district recorded the highest number of cases (187,322, 16.9%) and Ayawaso West district the lowest (1,739,
0.2%). Ashaiman district had the highest Annual parasitic incidence (API) per 1,000 population of 168.8 per 1000 population while Ablekuma Central district recorded the lowest API of 3.4 per 1000 population (Table 1). Generally, higher rates of malaria infection were observed in the north-eastern districts with low population densities, including Shai Osudoku, Ningo Prampram, Kpone Katamanso, Ashaiman and Adenta, whereas districts with higher population densities, located in the south-western part of the study area, were associated with lower malaria incidence (Fig. 2). The highest rainfalls were experienced in June while maximum temperatures were experienced in February. January was the month with the lowest minimum temperatures during the study period, except for 2016 and 2017 when August had the lowest minimum temperatures (Table 2).

Table 1
Total malaria case and API (cases per 1,000 population) stratified by districts (2015–2019)

<table>
<thead>
<tr>
<th>No.</th>
<th>Districts</th>
<th>Total malaria cases</th>
<th>Percentage</th>
<th>API*</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Adenta Municipal</td>
<td>69,758</td>
<td>6.3</td>
<td>156.1</td>
</tr>
<tr>
<td>2</td>
<td>Ledzokuku Municipal</td>
<td>39,394</td>
<td>3.6</td>
<td>49.7</td>
</tr>
<tr>
<td>3</td>
<td>Ada East</td>
<td>32,175</td>
<td>3.0</td>
<td>78.0</td>
</tr>
<tr>
<td>4</td>
<td>Shai Osudoku</td>
<td>48,989</td>
<td>4.4</td>
<td>164.2</td>
</tr>
<tr>
<td>5</td>
<td>Ada West</td>
<td>23,941</td>
<td>2.2</td>
<td>70.1</td>
</tr>
<tr>
<td>6</td>
<td>Ningo/Prampram</td>
<td>66,714</td>
<td>6.0</td>
<td>162.7</td>
</tr>
<tr>
<td>7</td>
<td>La Dade-Kotopon</td>
<td>17,437</td>
<td>1.6</td>
<td>16.4</td>
</tr>
<tr>
<td>8</td>
<td>La-Nkwantanang-Madina</td>
<td>51,889</td>
<td>4.7</td>
<td>80.2</td>
</tr>
<tr>
<td>9</td>
<td>Ga East</td>
<td>68,924</td>
<td>6.2</td>
<td>80.1</td>
</tr>
<tr>
<td>10</td>
<td>Ayawaso West</td>
<td>1,739</td>
<td>0.2</td>
<td>4.0</td>
</tr>
<tr>
<td>11</td>
<td>Ga South Municipal</td>
<td>57,602</td>
<td>5.2</td>
<td>36.3</td>
</tr>
<tr>
<td>12</td>
<td>Ga West Municipal</td>
<td>54,642</td>
<td>5.0</td>
<td>77.0</td>
</tr>
<tr>
<td>13</td>
<td>Ga Central Municipal</td>
<td>36,113</td>
<td>3.3</td>
<td>53.3</td>
</tr>
<tr>
<td>14</td>
<td>Tema West Municipal</td>
<td>6,369</td>
<td>0.6</td>
<td>9.6</td>
</tr>
<tr>
<td>15</td>
<td>Ashaiman Municipal</td>
<td>187,322</td>
<td>16.9</td>
<td>168.8</td>
</tr>
<tr>
<td>16</td>
<td>Kpone Katamanso</td>
<td>93,987</td>
<td>8.5</td>
<td>148.3</td>
</tr>
<tr>
<td>17</td>
<td>Ablekuma Central Municipal</td>
<td>3,355</td>
<td>0.3</td>
<td>3.4</td>
</tr>
<tr>
<td>18</td>
<td>Korle Klottey Municipal</td>
<td>20,227</td>
<td>1.8</td>
<td>26.5</td>
</tr>
<tr>
<td>19</td>
<td>Ablekuma North Municipal</td>
<td>11,356</td>
<td>1.0</td>
<td>12.6</td>
</tr>
<tr>
<td>20</td>
<td>Ayawaso North Municipal</td>
<td>10,142</td>
<td>0.9</td>
<td>22.4</td>
</tr>
<tr>
<td>21</td>
<td>Ayawaso East Municipal</td>
<td>5,981</td>
<td>0.5</td>
<td>9.9</td>
</tr>
<tr>
<td>22</td>
<td>Okaikei North Municipal</td>
<td>21,544</td>
<td>1.9</td>
<td>18.0</td>
</tr>
<tr>
<td>23</td>
<td>Ga North Municipal</td>
<td>49,129</td>
<td>4.4</td>
<td>84.6</td>
</tr>
<tr>
<td>24</td>
<td>Weija Gbawe Municipal</td>
<td>25,038</td>
<td>2.3</td>
<td>27.4</td>
</tr>
<tr>
<td>25</td>
<td>Krowor Municipal</td>
<td>6,241</td>
<td>0.6</td>
<td>11.8</td>
</tr>
<tr>
<td>26</td>
<td>Tema Metropolitan</td>
<td>16,993</td>
<td>1.5</td>
<td>16.5</td>
</tr>
<tr>
<td>27</td>
<td>Ablekuma West Municipal</td>
<td>13,122</td>
<td>1.2</td>
<td>13.7</td>
</tr>
<tr>
<td>28</td>
<td>Ayawaso Central Municipal</td>
<td>7,523</td>
<td>0.7</td>
<td>6.5</td>
</tr>
<tr>
<td>29</td>
<td>Accra Metropolis</td>
<td>57,724</td>
<td>5.2</td>
<td>22.3</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>1,105,370</td>
<td>100</td>
<td>1,630.1</td>
</tr>
</tbody>
</table>

*API- annual parasite incidence per 1,000 population
Table 2
Average monthly rainfall (mm), maximum temperature (°C) and minimum temperature (°C) in the Greater Accra Region from 2015–2019.

<table>
<thead>
<tr>
<th>Month</th>
<th>Average rainfall</th>
<th>Average max. temperature</th>
<th>Average min. temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>6.5</td>
<td>9.2</td>
<td>21.7</td>
</tr>
<tr>
<td>Feb</td>
<td>66.0</td>
<td>15.8</td>
<td>19.7</td>
</tr>
<tr>
<td>Mar</td>
<td>121.6</td>
<td>96.9</td>
<td>68.1</td>
</tr>
<tr>
<td>Apr</td>
<td>183.5</td>
<td>98.9</td>
<td>88.7</td>
</tr>
<tr>
<td>May</td>
<td>120.4</td>
<td>175.2</td>
<td>166.6</td>
</tr>
<tr>
<td>Jun</td>
<td>211.1</td>
<td>195.4</td>
<td>314.9</td>
</tr>
<tr>
<td>July</td>
<td>45.9</td>
<td>52.8</td>
<td>72.5</td>
</tr>
<tr>
<td>Aug</td>
<td>34.0</td>
<td>31.8</td>
<td>41.2</td>
</tr>
<tr>
<td>Sept</td>
<td>64.7</td>
<td>102.5</td>
<td>82.5</td>
</tr>
<tr>
<td>Oct</td>
<td>120.0</td>
<td>111.7</td>
<td>65.2</td>
</tr>
<tr>
<td>Nov</td>
<td>77.1</td>
<td>99.0</td>
<td>119.5</td>
</tr>
<tr>
<td>Dec</td>
<td>11.6</td>
<td>44.0</td>
<td>28.7</td>
</tr>
</tbody>
</table>

Time Series Decompositions

Time series decomposition analysis revealed seasonal patterns of malaria cases during the study period. Four peaks were observed, with the largest peak occurring in June of 2016 and 2017, and in July of 2015, 2018 and 2019. The three smaller peaks occurred in March, September, and October throughout the study period. The inter-annual pattern indicated a general increasing trend of cases, but with sharp fluctuations (Fig. 3).

Spatial Poison regression analysis

Model I with unstructured random effects only was the best-fit, most parsimonious model (as indicated by the lowest deviance information criterion [DIC]). Monthly malaria cases increased by 30% (95% credible interval [CrI]: 29–31%) per month during the study period. Results showed that the incidence of malaria increased by 0.1% (95% CrI: 0.02–0.16%) for every 1°C increase in monthly mean maximum temperature lagged at six months and 0.2% (95% CrI: 0.5–0.3%) for 1°C increase in monthly mean minimum temperature without lag during the study period. Rainfall on the other hand was not statistically significant in predicting malaria cases. After accounting for climatic covariates, there was no evidence of spatial dependency (Table 3 and Fig. 4a).
Table 3
Regression coefficients, relative risk and 95% credible interval from Bayesian spatial and non-spatial models of malaria in the Greater Accra Region, Ghana, January 2015-December 2019.

<table>
<thead>
<tr>
<th>Model/Variable</th>
<th>Coeff, posterior mean (95% CrI)</th>
<th>RR, posterior mean (95% CrI)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model I (Unstructured)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean monthly trend</td>
<td>0.262 (0.255, 0.269)</td>
<td>1.300 (1.290, 1.309)</td>
</tr>
<tr>
<td>Monthly rainfall (10 mm)*</td>
<td>1.87X10⁻⁷ (-5.46X10⁻⁶, 5.79X10⁻⁶)</td>
<td>1.000 (0.999, 1.000)</td>
</tr>
<tr>
<td>Monthly maximum Temp (°C) ‡</td>
<td>8.92X10⁻⁶ (1.73X10⁻⁴, 1.60X10⁻³)</td>
<td><strong>1.001 (1.0002, 1.0016)</strong></td>
</tr>
<tr>
<td>Monthly minimum Temp (°C) †</td>
<td>1.73X10⁻³ (5.15X10⁻⁴, 2.95X10⁻³)</td>
<td><strong>1.002 (1.0005, 1.0030)</strong></td>
</tr>
<tr>
<td>Heterogeneity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Structured (trend)</td>
<td>0.221 (0.120, 0.353)</td>
<td></td>
</tr>
<tr>
<td>Unstructured</td>
<td>1.22X10⁻⁴ (6.72X10⁻⁰⁵, 1.93X10⁻⁴)</td>
<td></td>
</tr>
<tr>
<td>DIC**</td>
<td>142747</td>
<td></td>
</tr>
<tr>
<td><strong>Model II (Structured)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean monthly trend</td>
<td>0.261 (0.254, 0.268)</td>
<td>1.298 (1.289, 1.307)</td>
</tr>
<tr>
<td>Monthly rainfall (10 mm)*</td>
<td>1.78X10⁻⁷ (-5.41X10⁻⁶, 5.76X10⁻⁶)</td>
<td>1.000 (0.9999, 1.000)</td>
</tr>
<tr>
<td>Monthly maximum Temp (°C) **</td>
<td>8.98X10⁻⁴ (1.88X10⁻⁴, 1.61X10⁻³)</td>
<td>1.001 (1.000, 1.002)</td>
</tr>
<tr>
<td>Monthly minimum Temp (°C) †</td>
<td>1.74X10⁻³ (5.27X10⁻⁴, 2.96X10⁻³)</td>
<td>1.002 (1.001, 1.003)</td>
</tr>
<tr>
<td>Heterogeneity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Structured (trend)</td>
<td>0.226 (0.123, 0.362)</td>
<td></td>
</tr>
<tr>
<td>Structured (spatial)</td>
<td>0.069 (0.038, 0.108)</td>
<td></td>
</tr>
<tr>
<td>DIC</td>
<td>142754</td>
<td></td>
</tr>
<tr>
<td><strong>Model III (Mixed)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean monthly trend</td>
<td>0.262 (0.255, 0.269)</td>
<td>1.300 (1.290, 1.309)</td>
</tr>
<tr>
<td>Monthly rainfall (10 mm)*</td>
<td>2.12X10⁻⁰⁷ (-5.43X10⁻⁶, 5.84X10⁻⁶)</td>
<td>1.000 (0.9999, 1.0000)</td>
</tr>
<tr>
<td>Monthly maximum Temp (°C) ‡</td>
<td>8.94X10⁻⁴ (1.81X10⁻⁴, 2.9X10⁻³)</td>
<td>1.001 (1.0002, 1.0016)</td>
</tr>
<tr>
<td>Monthly minimum Temp (°C) †</td>
<td>1.74X10⁻³ (5.27X10⁻⁴, 2.96X10⁻³)</td>
<td>1.002 (1.0005, 1.0030)</td>
</tr>
<tr>
<td>Heterogeneity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Structured (trend)</td>
<td>0.221 (0.120, 0.354)</td>
<td></td>
</tr>
<tr>
<td>Unstructured</td>
<td>2.1X10⁻⁴ (1.2X10⁻⁴, 3.2X10⁻⁴)</td>
<td></td>
</tr>
<tr>
<td>Structured (spatial)</td>
<td>6.76X10⁻⁵ (3.75X10⁻⁵, 1.1X10⁻⁴)</td>
<td></td>
</tr>
<tr>
<td>DIC</td>
<td>142757</td>
<td></td>
</tr>
</tbody>
</table>

* significant
** best-fit model; †Lagged one month, ‡Lagged six months
Abbreviations: coeff-coefficients; CrI-credible interval; RR-relative risk; DIC-deviation information criterion

In 24 districts, there was a >95% probability of a trend in the incidence of malaria cases higher than the regional trend. While only five districts had a >95% probability of malaria rates lower than the regional average and these were in the south-central part of the region (Fig. 4b).

**Discussion**
This study examined the spatio-temporal pattern of malaria transmission in the Greater Accra Region of Ghana utilizing data from the District Health Information and Management System (DHIMS). Malaria incidence varied across the region and increased over the study period with a strong seasonal pattern. The significant covariates of malaria transmission were maximum temperature lagged at 6 months and minimum temperature without lag. After accounting for the climatic variables, there was no significant residual spatial clustering.

The incidence of malaria was found to vary significantly between districts with only five out of the 29 districts located in the southcentral area having a lower trend than the regional average trend. Also, less urbanized districts were found to be associated with more cases and higher disease risk as compared to less urbanized districts. Previous studies have also found that lower incidence of malaria in more urban areas was related to greater social and economic development. Factors impacting on this finding include better housing and drainage systems as well as more accessible healthcare, resulting in decreased human vector contact and more active case management [12–14]. Populations in less urbanized areas are also more likely to be engaged in agricultural and other occupational activities leading to more exposure to mosquitoes, which breed in these areas [10, 15]. This study also showed a strong relationship between population density and malaria incidence as seen in Fig. 2. Districts with lower population densities tended to be less urbanized and correlated with a higher malaria incidence. This could be due to a lower ratio of humans to vectors in these districts, resulting in an increased biting rate [8, 16, 17].

There was a clear indication of seasonality and an irregular inter-annual pattern of malaria transmission in the Greater Accra Region; higher numbers of cases were recorded in the rainy seasons and in 2017 and 2019, respectively. However, rainfall was found to be statistically not significant in predicting malaria cases in this study, contradicting findings from previous studies [18, 19]. This might be a result of the tropical climate experienced in the study area, which ensures availability of aquatic habitats for breeding and humid conditions for mosquito survival are never limiting factors for malaria risk in this region. The decreasing number of cases in 2016 and 2018 could be due to the protection offered from the mass distribution of long lasting insecticide net (LLIN) in those years. However, LLIN was not included in this model.

Maximum temperature, lagged at six months, was positively correlated with malaria incidence. Similar findings were reported in other studies [20, 21]. The effects of increasing temperature on vector populations, the incubation period of malaria parasites and malaria transmission are well-known. Optimal temperature values from 23°C to 31°C usually favour malaria parasite development and vector survival, resulting in an increased malaria incidence [22]. However, the current study suggests a maximum temperature ranges of 33.7°C to 34.8°C lagged at 6 months positively affects malaria transmission. Also, other studies have recognised lagged climatic variables as being associated with malaria incidence over time. This is because lags serve as periods of habitat formation, vector development, infectivity and emergence of signs and symptoms in humans [23–25]. Nevertheless, it is also possible for the correlation observed in this study to be due to human behavioural factors during times of high temperatures such as not sleeping under LLINs, sleeping in the open or staying outdoors.

Minimum temperature ranges from 22.6°C to 23.0°C was associated with increased malaria cases. Minimum temperature was also found to affect the transmission of malaria in previous studies [26, 27]. The extrinsic incubation period (EIP) for Plasmodium falciparum was found to be 13 days at 25°C compared to 26 days at 20°C [28–31]. Therefore, it can be inferred from the findings of this study that EIP is likely to reduce at temperatures above 20°C resulting in the rapid development of the parasite, increased biting rate and increased malaria transmission.

**Study limitations**

Findings from this study need to be interpreted with the consideration of some limitations. Firstly, data were not available to measure the availability, accessibility and usage of malaria control and prevention strategies (LLIN, IPTp, IRS) in the region. Hence, these were not included in the model. Secondly, the study used passive surveillance data, for which the quality and reliability could not be readily ascertained. Lastly, unmeasured risk modifiers including living standards and socio-economic development, treatment seeking behaviours and population mobility were unaccounted for in this study. The influence of these characteristics on malaria transmission has been identified in previous studies [32–35], and future studies should explore the connection between malaria and these factors by including them in the analysis.

**Conclusions**

Findings from this study showed a positive correlation between malaria and climatic variables (maximum and minimum temperature) in the Greater Accra Region of Ghana from 2015–2019. Malaria transmission was heterogeneous across the districts and showed strong seasonal and inter-annual variations. These findings are can be used for focused malaria control and prevention interventions to these high-risk districts by increaseng LLINs, IRS and IPTp. Especially, during periods identified to be associated with high malaria transmissions.

**Methods**

**Study area**

The study was conducted in the Greater Accra Region, which includes the country’s capital city, Accra (Figure 1). It is the smallest of the 16 administrative regions in Ghana. The area is about 3,245 square kilometers and it is the second-most populated region in the country with a population of 5,055,765 in 2019 [36]. It is divided into 29 local government areas (LGAs). Most of the LGAs are urban and urban LGAs house more
than 80% of the region's residents [37]. The LGAs are classified as districts, municipalities and metropolitan areas, with metropolitan areas being the most urban. However, for the purpose of this study, they are all referred to as districts. The blend of remote and urban communities within the region makes it a suitable site for this study. The climate of the area is categorized as tropical savannah.

Data source
The study used secondary aggregated clinical data for all age groups, including both in-patients and outpatients with laboratory-confirmed malaria infections from 2015–2019 in the Greater Accra Region. A total of 1,105,370 malaria cases were identified through passive case detection at health facilities and collated in the DHIMS at the district level. Yearly population data for each district were obtained from the Health Information Department of Greater Accra Regional Health Directorate.

Long-term average annual and seasonal temperature and rainfall variables were determined using data obtained from the WorldClim project at a spatial resolution of 1 km [38]. The variables obtained from WorldClim had been created by spatial interpolation of climate data gathered from global weather station sources between 2010 and 2018 utilising a thin-plate smoothing spline algorithm.

Polygon shapefiles of administrative boundaries at the district level of the Greater Accra Region were obtained from the DIVA-GIS website (www.diva-gis.org). The spatial datasets including Standard Morbidity Ratios of malaria cases were imported into ArcGIS version 10.7.1 (ESRI Inc. Redlands, CA, USA, URL: https://www.esri.com) and projected to the Universal Transverse Mercator (UTM) coordinate system (zone 48 N).

Analysis of seasonal and inter-annual patterns
The mean monthly number of malaria cases was calculated from the full-time series (January 2015–December 2019). Seasonal-trend decomposition, based on locally (STL) weighted regression was used to decompose the time series of malaria incidence to reveal the seasonal relationship, inter-annual pattern, and the residual variability. The STL model was structured as follows:

\[ Y_t = S_t + T_t + R_t \]

where \(Y_t\), \(S_t\), \(T_t\) and \(R_t\) represent the local malaria cases with logarithmic transformation, additive seasonal component, trend, and remainder component respectively while \(t\) signifies time in months [35, 39, 40].

Standardized morbidity ratios
Standardized morbidity ratios (SMRs) per district were analysed using the following formula:

\[ Y_i = \frac{O_i}{E_i} \times 100 \]

Where \(Y\) denotes the total SMR in district \(i\), \(O\) and \(E\) are the total number of the observed and expected malaria cases in district \(i\) across the study period. The expected number (E) was calculated by multiplying the regional malaria incidence by the average population for each district over the study period.

Annual parasitic incidence
Annual parasitic incidence (API) per district were calculated using the formula:

\[ \text{Annual Parasitic Incidence (API)} = \frac{\text{Total No. of Malaria Cases in a Year}}{\text{Total Population}} \times 1000 \]

Independent climatic variable selection
A preliminary Poisson regression was used to select the significant climatic covariates. Maximum and minimum temperature, and rainfall with zero, one, two, three, four, five and six-month lag times, were entered into univariate Poisson models. Significant (p<0.05) climatic variables with lag times
with the lowest Akaike’s information criterion (AIC) were selected for inclusion in the model (Supple Table 1). The co-linearity of selected variables was tested using variance inflation factors (VIF) (Supple Table 2). Minimum temperature without lag, rainfall lagged at one month and maximum temperature lagged at six months were selected. Preliminary statistical analyses were all performed using the STATA software version 16.0 (Stata Corporation, College Station, TX, USA, URL: https://www.stata.com).

**Spatio-temporal model**

Poisson regression models for malaria cases were created using the Bayesian statistical software WinBUGS version 1.4 (Medical Research Council, Cambridge, UK and Imperial College London, UK). Three models were created incorporating, spatially unstructured (Model I), spatially structured (Model II) and both structured and unstructured random effects (Model III). Each model included the climatic variables as fixed effects. The best-fit parsimonious model was selected with the lowest DIC. Model III, which includes all components of the other models was structured as follows:

\[ Y_i \sim \text{Poisson} \left( \mu_i \right) \]

\[ \log \left( \mu_i \right) = \log \left( E_i \right) + \theta_i \]

\[ \theta_i = \alpha + \beta_1 \times \text{trend}_i + \beta_2 \times \text{rainfall}_i + \beta_3 \times \text{max temp}_i + \beta_4 \times \text{min temp}_i + u_i + s_i + w_i \]

where \( Y \) are the observed counts of malaria, for \( i^{th} \) district \((i=1...60)\) in the \( j^{th} \) month (January 2015 to December 2019), \( E \) are the expected number of malaria cases included as an offset to control for population size and \( \theta \) is the mean log relative risk (RR); \( \alpha \) is the intercept, and \( \beta_1, \beta_2, \beta_3, \beta_4 \) are the coefficients for monthly malaria trend, rainfall lagged at one month, maximum temperature lagged at six months and minimum temperature without lag. The unstructured and spatially structured random effects were represented by \( u_i \) and \( s_i \), each with a mean of zero and with variances of \( \sigma_u^2 \) and \( \sigma_s^2 \) and \( w_{ij} \) is the spatiotemporal random effect (with a mean of zero and variance of \( \sigma_w^2 \)).

The spatially structured random effect was calculated using a conditional autoregressive (CAR) prior structure. Spatial relationships between the districts were computed using queen contiguity, where an adjacency weight of 1 was allocated if two districts have a common border or vertex and 0 if they did not. The intercept was delineated with a flat prior distribution, while the coefficients were defined by a normal prior distribution. Non-informative gamma distributions characterise by shape and scale parameters equivalent to 0.01 were used to specify priors for the precision (1/ \( \sigma_u^2 \) and 1/ \( \sigma_s^2 \)) of the unstructured and spatially structured random effects. Additionally, models were established without the structured (Model I) and unstructured (Model II) random effects to determine if including them improved model fit.

The burn-in, comprising the initial 10,000 iterations, were discarded. The simulation chains were then run for blocks of 20,000 iterations to assess for convergence. Convergence was determined through visual inspection of posterior density and history plots for each model and was achieved at 100,000 iterations. Markov Chain Monte Carlo simulation with Gibbs sampling was used to estimate model parameters [41]. Values of the posterior distributions were then stored and summarised for analysis (posterior mean and 95% CrI).

An \( \alpha \)-level of 0.05 was used to indicate statistical significance (as shown by 95% CrI for coefficients of \( \beta \) that excluded 0). ArcMap 10.7.1 software (ESRI, Redlands, CA, URL: https://www.esri.com) was used to produce maps of the posterior means of the random effects from the three models.

**Ethical considerations**

Ethical approval for the study was obtained from the Human Research Ethics Committee of the Australian National University (Protocol: 2020/465). Permission for the study was also granted by the Ethics Review committee of the Ghana Health Service (protocol: GHS-ERC 051/07/20). The study was conducted in accordance with guidelines and regulations from the above two ethic committees regarding the use of secondary data. The Greater Accra Regional Health Directorate also approved and provided the malaria dataset for the conduct of the study within the region. The dataset provided did not include any personally identifying information and could not be linked back to study participants by the authors.

**List Of Abbreviations**

- AIC: Akaike’s information criterion
- API: Annual parasitic incidence
- BIC: Bayesian information criterion
- CAR: Conditional autoregressive
CrI: Credible interval  
DHIMS: District Health Information and Management System  
DIC: Deviance information criterion  
EIP: extrinsic incubation period  
GAR: Greater Accra Region  
LGAs: Local Government Areas  
IPTp: Intermittent Preventive Treatment in pregnancy  
IRS: indoor residual spraying  
LLIN: long lasting insecticide net  
MCMC: Markov chain Monte Carlo  
RR: Relative risk  
SMR: Standardised morbidity ratios  
STL: Seasonal-trend decomposition, based on locally  
VIF: Variance inflation factors  
WHO: World Health Organization  

**Declarations**

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**Authors contribution**

ED and KW were involved in the conception of the study. ED undertook literature review, did the analysis and drafted the manuscript. KW assisted in the analysis, interpretation of results and provided critical comments of the manuscript. CE assisted with ethics acquisition. CA obtained the data. MK, ACAC and DJG critically reviewed and edited the manuscript. All authors read and approved the final manuscript.

**Competing interests**

The authors declare that they have no competing interests.

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**Availability of data and materials**

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

**Author's information**

The authors would like to clarify that all the views and opinions expressed in the manuscript are theirs and do not represent the views of the Australian Government.

**References**


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Figures


**Figure 1**

Metropolitan, 27- Ablekuma West Municipal, 28- Ayawaso Central Municipal & 29- Accra Metropolis. (Map was created by importing polygon shapefiles of administrative boundaries at the district level of the Greater Accra Region obtained freely from the DIVA-GIS website, URL: https://www.diva-gis.org and based files obtained from google maps, URL: https://www.google.com/maps/ into ArcMap 10.7.1 software, URL: https://www.esri.com by the first author).

Figure 2

Standard morbidity ratios (SMRs) and population densities (PDs) per square km by districts in the Greater Accra Region from 2015-2019. SMRs are indicated with colours with the darker colours showing districts with higher ratios. PDs per districts are shown with dark circles, the larger the circle, the higher the densities. Urban, semi-urban and rural areas are demarcated with red, blue and yellow lines respectively. (Map was created by importing polygon shapefiles of administrative boundaries at the district level of the Greater Accra Region obtained freely from the DIVA-GIS website, URL: https://www.diva-gis.org and the spatial datasets including SMRs of malaria cases and PDs into ArcMap 10.7.1 software, URL: https://www.esri.com by the first author).
Figure 3
Temporal decomposition of numbers of malaria cases for Greater Accra Region, 2015–2019 utilising Seasonal-trend decomposition, based on locally (STL) weighted regression.
Figure 4

Spatial poisson regression analysis. (a) Unstructured random effects of malaria in Model I; (b) Trend analysis during the study period, 2015-2019. (Maps were created by importing polygon shapefiles of administrative boundaries at the district level of the Greater Accra Region obtained freely from the DIVA-GIS website, URL: https://www.diva-gis.org into ArcMap 10.7.1 software, URL: https://www.esri.com and the Bayesian statistical software WinBUGS 1.4, URL: https://www.mrc-bsu.cam.ac.uk/bugs/ by the first and seventh authors).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Supplementarymaterials.pdf