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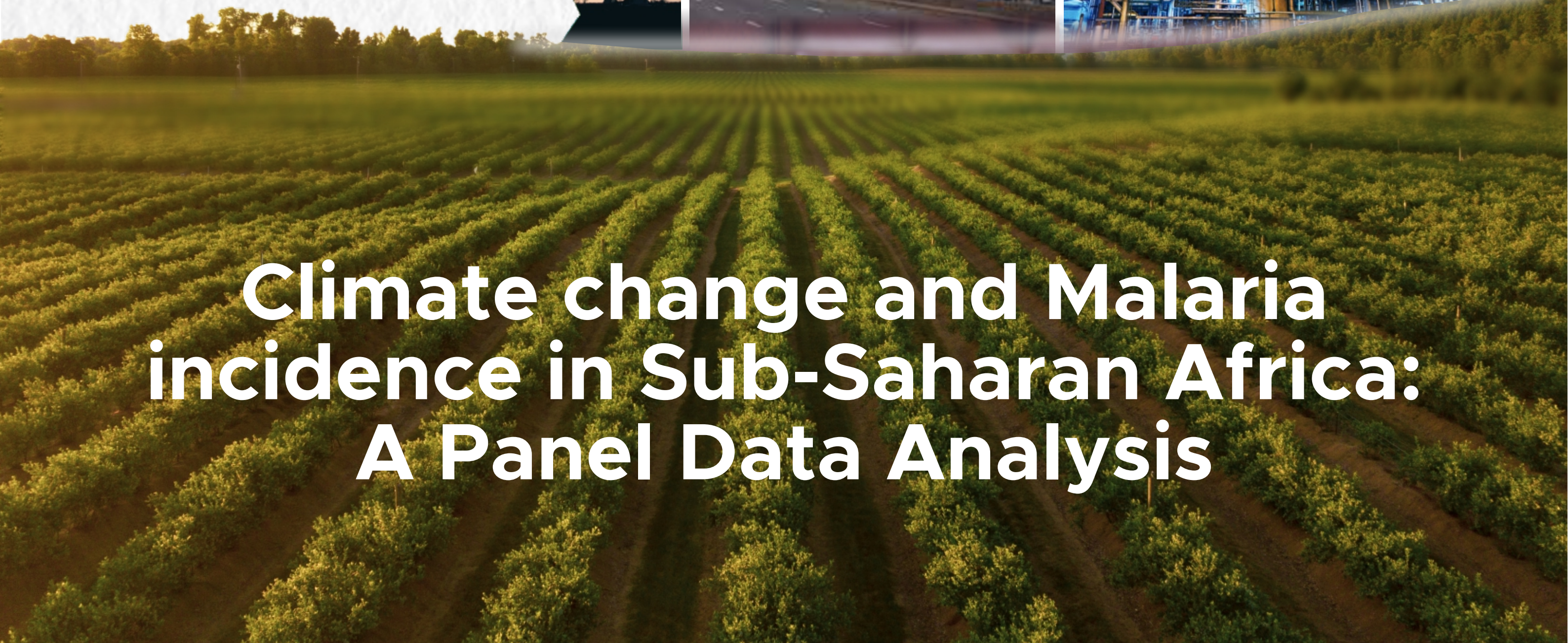

Climate change and Malaria incidence in Sub-Saharan Africa: A Panel Data Analysis

Climate change and Malaria incidence in Sub-Saharan Africa: A Panel Data Analysis

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Abstract

Despite all the efforts that countries in SSA have made to eliminate the disease in collaboration with other countries, as well as advancements in controlling and curing it, the disease still poses a health challenge in the region. According to different reports, the incidence of the disease increased in the entire world in the years 2020 and 2021, reaching 241 million in the year 2020 from 227 million in the year 2019, indicating that over 200 million instances of the disease were reported in the SSA region alone, resulting in a total of 403,000 deaths, mostly among children below the age of five (WHO, 2021). While the health sector's restrictions resulting from the COVID-19 pandemic are attributed to rising disease cases, everyone agrees that the leading cause of the increase in disease incidence in the region is the global warming phenomenon. Rising temperatures, changes in rainfall patterns, increased humidity, and the frequency of extreme weather events have created conducive breeding environments for mosquitoes, facilitating the development of malaria parasites and expanding transmission zones and seasons (IPCC, 2022; Caminade et al., 2019). However, there is limited, dispersed, and bounded empirical evidence documenting the long-run relationship between climate change and malaria incidence in SSA regions, as most studies are based on specific areas, creating uncertainty for the formulation of climate-responsive malaria policy options. Thus, this research aims to investigate the effects of climate change on malaria incidence in SSA using panel data from 2010 to 2024.

The study employed the Generalised Method of Moments (GMM) for the data estimation. The findings revealed statistically significant positive coefficients for climate, pneumonia, and GDP per capita, indicating that malaria incidence increases with climate change. The results also suggest that food insecurity does not significantly affect malaria prevalence. The study recommends incorporating climate-related factors into malaria control and prevention strategies. Monitoring weather patterns, identifying high-risk areas based on climatic conditions, and implementing targeted interventions to reduce mosquito breeding and malaria transmission should be accorded the utmost priority.

Keywords: Climate change, malaria incidence, generalised method of moments, sub-Saharan Africa

JEL Classification: Q54, Q56, 112, 118, C13, C21, 055

1.0 Introduction

Malaria remains a public health concern in sub-Saharan Africa (SSA), with the WHO African Region still bearing most of the global malaria disease burden. According to the World Health Organisation (2024), in 2023, an estimated 263 million cases of malaria occurred globally, of which 94% of all malaria and 95% of malaria deaths occurred in the WHO African Region, resulting in an estimated 597,000 deaths. Children under the age of five years remain the most vulnerable group and contribute nearly 76% to the deaths from malaria in Africa (WHO, 2024). Among the affected nations, Nigeria is most impacted and contributes to nearly 30.9% of malaria-related deaths and boasts one of the highest levels of case prevalence globally (Target Malaria, 2024).

Until late 2024 and into 2025, malaria control operations in SSA continue to face several challenges. Reports by The Guardian (2024) and Malaria Consortium (2024) indicate that several factors, including insecticide and drug resistance, climate change, constrained funding, and weak health infrastructure, are driving rising case levels. In December 2024, Nigeria introduced the malaria vaccine into its national immunisation program, a significant achievement in the country's malaria control program (Gavi, 2024). Fresh outbreaks, however, persist across the region. For instance, early in 2025, Équateur Province in the Democratic Republic of the Congo observed an outbreak of nearly 1,100 cases and about 60 deaths of malaria, which indicates ongoing transmission risks (Reuters, 2025). Such occurrences reaffirm that malaria is far from being eliminated in SSA, underscoring the imperative for continued investment in novel vector control technologies and stronger public health institutions to alleviate its devastating effects.

According to the WHO (2020), the number of malaria infections in Africa decreased by 38% between 2000 and 2019, from 363 to 225 cases per 1000 at-risk individuals. Meanwhile, there were 40 instances of malaria reported for every 100,000 people considered to be at risk, which is a 67% decrease from the 121 cases of malaria-related deaths. Due to COVID-19-related disruptions to malaria services, the number of cases per 1000 at-risk persons increased to 232 in 2020 (WHO, 2020). Between 2000 and 2015, the incidence of malaria in Southern African countries decreased by 50%, but the number of cases leading to clinical illness decreased by 40% during the same period. It was estimated that the broad adoption of malaria-preventive methods accounted for 68% to 78% of the benefits. These tactics included insecticide-treated nets, indoor residual spraying (IRS), long-lasting insecticide-treated nets (LLINs), early diagnosis, and potent antimalarial medications.

However, recently, the pace of advancement has slowed and, in some cases, even reversed (WHO, 2020). To control and eliminate malaria, Mswati et al. (2019) argue that the current approach is constrained by several factors, including the development of artemisinin partial resistance (WHO, 2021), the widespread and growing resistance to pyrethroid-based vector control, and funding shortages. The amount allocated to combat malaria decreased to $3.0 billion in 2019 from $3.2 billion in 2017. Compared with the $56 billion estimated annually to meet the objectives of the WHO global malaria strategy, this is a considerable reduction (WHO, 2020). The increasing frequency of malaria is directly attributable to underfunding. Insufficient funding makes it challenging to implement necessary preventive and control measures—such as healthcare services and mosquito control. Developing new strategies to combat malaria is challenging due to a lack of creativity, inadequate research, and inadequate surveillance and monitoring systems. The lack of education and awareness campaigns makes it harder for people to alter their behaviour and become involved in the community, which feeds the cycle of transmission.

The establishment of measures to control and eradicate the disease among the member states of SSA, coupled with efforts by various member states and other countries, has not helped eliminate the threat to the health and lives of the people of the region. According to multiple reports, the prevalence of the disease increased across the whole world in the years 2020 and 2021, reaching 241 million in the year 2020 compared to 227 million in the year 2019, which means that over 200 million cases of the disease were registered in the SSA region, leading to a total of 403,000 deaths, mostly among young children below the age of five (WHO, 2021). While the restrictions in the health field caused by the COVID-19 pandemic are the blamed factor, everyone would agree on the believed reasons. From the above discussions, the central belief is that the leading cause of the increase in the region's disease incidence is the growing threat of global warming.

The increased temperatures, rainfall patterns, humidity levels, and frequency of extreme weather patterns created better conditions for the breeding habits of mosquitoes, hence the development of the malaria parasite, thus creating conditions for the expansion of transmission zones and the expansion of the transmission season (IPCC, 2022; Caminade et al., 2019). In summary, there is a lack of empirical evidence on the long-run relationship of the effects of climate change on the incidence of malaria in SSA regions, as studies were primarily conducted for the regions, creating room for uncertainties in the formulation of policy for the effectiveness of the responses to the effects of climate change on the incidence of malaria in the region. This study examined the impact of climate change on malaria incidence in SSA regions from 2010 to 2024.

Also, Several studies have shown the influence of climate on malaria transmission; an increased incidence of the illness has been associated with moderate temperatures and precipitation (Hoshen et al., 2004; Singh & Morse, 2002). According to Paaijmans (2009), rainfall affects the spread of malaria by creating many mosquito breeding grounds. As a result, the incidence of malaria increases worldwide in direct proportion to precipitation levels. However, the effects of severe rain are negligible (Singh & Morse, 2002). Malaria spreads faster or less swiftly depending on temperature fluctuations (Newman & Networks, 2010). In fact, temperature and other weather-related factors are expected to have a non-linear relationship with malaria incidence. Stated differently, one would expect a positive correlation between the malaria prevalence and the weather.

Apart from this, regression analysis has not been used to examine how climate change affects malaria incidence in Sub-Saharan Africa. Diouf, Adeola, Abiodun, Lennard, Shirinde, Yaka, and Gbobaniyi used box-and-whisker plots in 2022 to examine the average annual incidence of malaria across different climate epochs and emission scenarios. Gafna, Obando, Kalwij, Dolos, and Schmidtlein (2023) also used species distribution modelling (SDM) to look into the distribution of plant species that both stop and spread malaria, as well as the possible effects of future climate change on these distributions. Regression analysis is utilised in this paper to evaluate the impact of climate change on malaria incidence, thereby addressing the observed gap.

The rest of the paper is highlighted as follows: Section two encompasses the literature review, while Section three accommodates the methodology. The results and discussion are presented in Section 4, and Section 5 concludes the paper.

2.0 Literature Review

2.1 Conceptual Review

2.1.1 Climate change and malaria incidence

Climate change is the gradual modification of the Earth's regular changes of weather, including temperature, precipitation, wind direction, and other elements of the climate. These changes are largely the result of both natural processes and human activities, including deforestation and the burning of fossil fuels, resulting in the emission of huge amounts of greenhouse gases into the atmosphere. This, therefore, accelerates global warming, causing changes to the climate and resulting in extreme changes to the weather. Climatic changes have many implications for the Earth, including ecosystems, agriculture, and human health.

Incidence of Malaria**;** Malaria incidence rates refer to the rates of new malaria cases reported in a specified population and area in a specified period. Malaria is a mosquito-borne infectious disease caused by Plasmodium parasites. Malaria is transmitted to humans through the bites of infected female Anopheles mosquitoes. Malaria is a public health problem in many parts of the world and is prevalent in tropical and subtropical regions. The climate in these regions is conducive for the breeding and survival of mosquitoes. The World Health Organization reported in 2021 that malaria is a critical threat to human health and is responsible for high rates of mortality and morbidity. The relationship between malaria and climate change is also a public health concern.

2.1.2 Rising threat of malaria in sub-Saharan Africa

Malaria continues to be one of the most dangerous vector-borne diseases in Sub-Saharan Africa, despite recent national and international efforts to tackle it (Badmos et al., 2021). Over 90% of malaria-related deaths occur in tropical regions of sub-Saharan Africa, since malaria is primarily a problem in developing tropical or sub-tropical nations (UNICEF, 2019). According to Badmos et al. (2021), out of an estimated 229 million cases, 409,000 persons worldwide passed away in 2019 from malaria-related causes. Ninety per cent of the 409,000 documented deaths took place in Sub-Saharan Africa (SSA), with 29 SSA countries accounting for about ninety-five per cent of the cases (WHO, 2020). More than half of all cases globally were found in Nigeria (27%), the Democratic Republic of the Congo (12%), Uganda (5%), Angola (3.4%), Burkina Faso (3.4%), and Mozambique (4%) (W.H.O., 2021). Malaria claims the life of a child under five every two minutes; young children and pregnant women are often the most vulnerable populations (Schantz-Dunn & Nour, 2009). In the WHO African region, exposure to pregnancy-related malaria has been associated with low birth weights, morbidities, and even fetal mortality (WHO, 2020).

2.1.3 Ongoing interventions used for malaria prevention and challenges

Over the last 20 years, several malaria control programs have been implemented in SSA countries where the disease is prevalent. A few examples of preventative chemotherapeutic approaches include seasonal malaria chemoprevention (SMC) for children under five, intermittent preventive treatment of pregnant women (IPTp), and intermittent preventive treatment of infants (IPTi). It also includes an artemisinin combination therapy (ACT) treatment package, long-lasting insecticide-treated nets (LLIN), and residual indoor spraying. Mosquirix, the most recent malaria immunisation vaccine, is now available. The World Health Organisation's African region failed to meet the 25% and 20% targets for malaria mortality and morbidity, respectively, set out in the 2020 Global Technical Strategy (WHO, 2021). Despite this, South Africa's malaria burden has significantly decreased as a result of these initiatives.

2.1.4. Malaria vaccine

The WHO approved RTS-S (Mosquirix) as the first malaria vaccine in 2021, following successful pilot trials in three (3) SSA countries: Kenya, Ghana, and Malawi. During the trial, almost 830,000 children received vaccines, resulting in a 40% reduction in malaria incidence and a 30% reduction in hospital admissions for severe malaria. Estimates of the worldwide mosquito coverage suggest that tens of thousands of lives may be spared annually. Nonetheless, problems with the supply chain, waning immunity, and budgetary constraints continue to prevent malaria vaccines from being widely used (Rodrigues et al., 2020).

2.2 Theoretical Review

2.2.1 Transmission Dynamics Theory:

The spread dynamics theory shows how mosquitoes, the environment, and the disease interact in complex ways to increase the likelihood of malaria transmission. According to this theory, temperature and humidity play a significant role in the development and survival of the Plasmodium parasite and the Anopheles mosquito vector. Warmer weather and higher humidity may hasten the development of parasites and mosquitoes, thereby enhancing the efficiency of malaria transmission.

In the context of changing weather patterns, monitoring and predicting malaria outbreaks require an understanding of transmission dynamics. Concerns about mosquito vector habitats expanding into previously non-endemic areas are growing as rising temperatures from climate change push them farther north. Planned vector control and public health interventions may be affected by variations in the length and intensity of malaria seasons. These variations may result from changes in transmission patterns. Combining meteorological data with epidemiological models based on this theory may thus enhance our ability to reduce the burden of malaria by forecasting transmission patterns in a changing environment (Rogers & Randolph, 2000).

2.2.2 Kuznet Hypothesis

The original theory by economist Simon Kuznets predicted a reverse U-shaped relationship between economic growth and income disparity. This hypothesis might further our knowledge of the potential effects of economic growth on environmental variables and public health outcomes related to malaria incidence and climate change in Sub-Saharan Africa.

First of all, there is no denying that the expansion of industry, urbanisation, and deforestation were hallmarks of Sub-Saharan Africa's early economic boom. Because of their increasing greenhouse gas emissions, these activities have the potential to harm the environment, hasten climate change, and alter land use. As long as economic development continues, nations may adopt more sustainable, environmentally friendly practices. However, this phenomenon is often associated with growing economic disparities. To effectively address the challenges posed by climate change, research by Ssempiira et al. (2016) emphasises the importance of policies that support sustainable development and minimise environmental impact during the early phases of economic expansion.

Second, as Sub-Saharan African countries move up the economic development curve, there is a noticeable variation in malaria prevalence. Growing gaps in wealth result in uneven access to healthcare, hygienic environments, and clean water, all of which raise the risk of malaria infection among people experiencing poverty. On the other hand, sustained economic development might contribute to reducing these inequities by funding public health facilities and disease-prevention initiatives. Thus, Orem et al.'s 2019 study in Uganda, which examined the association between economic development, expanding access to healthcare, and reduced malaria prevalence, verified the Kuznets Hypothesis.

The Kuznets Hypothesis is used to examine the relationship between malaria prevalence and climatic change in Sub-Saharan Africa, shedding light on the intricate links between social inequality, economic development, and environmental and public health outcomes. Growing socioeconomic inequality may negatively affect malaria incidence, just as early economic growth may hasten climate change. However, as countries go up the development curve, targeted programmes and financial investments in sustainability and public health could yield greater outcomes. Sub-Saharan African countries must repress this tendency to prevent malaria and mitigate the adverse effects of economic inequality.

2.3 Empirical Review

This section of the study reviews the empirical findings of earlier studies in this area. For instance, in contrast to an actual assessment period (1981–2010), Diouf (2022) examined the potential effects of climate change on malaria in West Africa in the near future (2006–2035) and the distant future (2036–2065) under two representative concentration pathway (RCP) scenarios (RCP4.5 and RCP8.5). Using the coordinated regional downscaling experiment (CORDEX), simulations of the Rossby Centre Regional Atmospheric Climate Model (RCA4) were used to forecast temperature and precipitation. The malaria model used is the Liverpool Malaria Model (LMM), a dynamic model driven by daily rainfall and temperature time series derived from CORDEX data. The results demonstrate a unimodal distribution of malaria incidence, along with significant seasonal variation in malaria transmission associated with rainfall patterns unique to latitude. The mean annual prevalence of malaria should decline in both RCPs, though more sharply in RCP8.5. According to the research, the average prevalence of malaria during the reference period was greater than predicted in six out of the eight downscaled GCMs. The results of this research contribute to our knowledge of the effects of malaria in the RCP4.5 and RCP8.5 emission scenarios. According to these results, West Africa's southern region is the most susceptible to malaria, and more collaboration and effort are needed from all parties involved to ensure that funding is allocated to combat the illness.

The effect of climate change on Kenya's supply of antimalarial plants is examined in Gafna (2023). Antimalarial herbs are often utilised as a first-line therapy for malaria in many rural parts of East Africa. The findings indicate that the three environmental factors with the most significant effect on the distribution of antimalarial species were the mean temperature of the hottest quarter, the amount of precipitation in the wettest quarter, and the mean temperature of the coldest quarter. According to the climate change scenarios SSP2-4.5 and

SSP5-8.5, the habitat of antimalarial species would have significantly decreased in certain places while expanding or remaining steady in others between 2050 and 2070. Different areas will see different effects from climate change. By the 2050s and 2070s, the majority of our scenarios suggest that over half of the antimalarial species would be vulnerable or endangered. Future malaria cases are expected to be lower, but the conditions that allow the malaria virus to thrive should be more favourable to the species that harbours it. Geographically targeted conservation measures and additional control operations against malaria vectors are especially crucial since the availability of antimalarial species will decrease in areas where malaria vectors are prevalent.

In the study titled "Climate Extremes and Malaria Incidence in Tropical Africa" conducted by Ayanlade, Radeny, and Morton (2020), the researchers studied a sample comprising 1200 district-level observations from 15 countries in sub-Saharan Africa. They applied the dynamic panel model and the Generalised Method of Moments (GMM) approach to observe the impacts of climate-related events. The study concluded that the heat waves and heavy rainfall have a significant effect on the increase in the number of breeding mosquitoes and the subsequent cases of malaria outbreaks. The study further concluded that the adverse climate impacted the existing malaria control mechanisms, resulting in the recurring cases of the disease.

Omonijo, Mordi, and Ayanlade (2021) conducted a study titled "Weather Variability and Malaria Prevalence in Sub-Saharan Africa" using a sample of 28 countries from various countries through a fixed effect model, as well as a random effect model. The study indicated that moderate levels of temperature increase and seasonal rains were strongly correlated to the increase of malaria cases, especially among rural communities. Additionally, the study indicated that lack of access to healthcare facilities heightened the effects of climate change.

3.0 Methodology

3.1 Theoretical Framework

Transmission Dynamics Theory

Transmission Dynamics Theory serves as the foundation for this research. The theory provides a systematic framework for understanding the complex interactions between malaria prevalence, mosquito behaviour, and climate change in Sub-Saharan Africa. This section models the number of mosquitoes (M_{ijt}) in a given country (i), area (j), and time period (t). Two key elements affecting mosquito dynamics are temperature (T_{ijt}) and precipitation (P_{ijt}). The mosquito population change over time is expressed mathematically as follows:

$$\frac{dM_{ijt}}{dt} = \alpha + \beta_t T_{ijt} - \beta_2 P_{ijt} + \mathcal{E}_{t\_}(ijt) \qquad (1)$$

In this equation, a represents the initial growth rate, β_1 and β_2 denote the effects of temperature and precipitation, respectively, while ε_1_{ijt} captures random fluctuations in mosquito population dynamics (Smith, 2004).

Transmission Dynamics of Malaria

This section examines the malaria incidence rate (Y_{ijt}) within the same national and regional context. In addition to temperature, mosquito density (M_{ijt}) is directly associated with malaria transmission. The kinetics of malaria transmission can be represented as follows:

$$Y\_(ijt) = y_0 + y_1 M\_\ (ijt) + y_2 T\_(ijt) + \acute{\eta}\_(ijt) \qquad (2)$$

In this model, γ_0 denotes the intercept, γ_1 and γ_2 represent the effects of mosquito density and temperature, respectively, while η_{ijt} captures unobserved factors influencing malaria transmission.

3.2 Model specification

This research focuses on how climate change affects malaria incidence in Sub-Saharan Africa. The study used panel data analysis because it was inspired by Diouf et al.'s (2022) work, which likewise examined the potential effects of future climate change on malaria in West Africa. In view of this, the study's model said the following:

$$incidence - of - malaria = \emptyset_0 + \emptyset_1 CLIMATE_{it} + \emptyset_2 P\_anemia_{it} + \emptyset_3 GDPPC_{it} + \emptyset_4 food\_insecurity_{it} + \varepsilon$$

eq. 1

Where;
GDPPC indicates GDP per capita income,
Malaria incidence represents the number of malaria cases.
Climate represents climate change,
$\emptyset_1 - \emptyset_0$The slopes of the independent variables represent Anaemia.
$\emptyset_0$ represents Constant.
ε=Stochastic variable

3.3 Source of Data

The data used in the study, spanning 20010 to 2024, were sourced from the World Bank Development Index, 2025 version. Data availability informed the selection of countries for the study of the selected variables. A total of 36 sub-Saharan African counties were selected. The selected countries are shown in the Table below.

SSA countries

Angola	Equatorial Guinea	Malawi	Somalia
Benin	Eritrea	Mali	South Africa
Botswana	Eswatini	Mauritania	South Sudan
Burkina Faso	Ethiopia	Mauritius	Sudan
Burundi	Gabon	Mozambique	Tanzania
Cabo Verde	The Gambia, the	Namibia	Togo
Cameroon	Ghana	Niger	Uganda
Central African Republic	Guinea	Nigeria	Zambia
Chad	Guinea-Bissau	Rwanda	Zimbabwe
Comoros	Kenya	Sao Tome and Principe	
Congo, Dem. Rep.	Lesotho	Senegal	
Congo, Rep.	Liberia	Seychelles	
Cote d'Ivoire	Madagascar	Sierra Leone	

Source: Author, 2025

Note: The shaded countries were excepted due to data availability.

3.4 Estimation Techniques

Generalised method of moments (GMM) estimators were developed by Holtz-Eakin et al. (1990), Arellano and Bond (1991), and Arellano and Bover (1995) for dynamic panel-data models. The presence of endogenous right-side components dictates which GMM to use, and the estimator reliably yields parameter estimates by accounting for the endogeneity of the lag-dependent variable. Furthermore, it allows for autocorrelation, fixed effects, and heteroskedasticity within each nation for each person (Roodman, 2009). Arellano-Bond performs better than the Arellano-Bover/Blundell-Bond estimator when the scenario with no correlation between the initial differences in the instrument variables and the fixed effects is considered. More equipment is employed in this procedure to boost its effectiveness.

4.0 Results and Discussion

4.1 Panel Unit Root Test

To determine if a time series variable has a unit root or is non-stationary, panel data is subjected to a statistical method known as a panel unit root test. Panel data are observations gathered across a range of time periods from several sources (cross-sectional units). The unit root test aims to determine whether the variable under examination exhibits a stochastic trend or is stationary across the entire panel, enabling efficient statistical inference and modelling.

Table 1: Panel Unit Root Test at Level

	Level			**First Difference**		
	None	**Intercept**	**Intercept & Trend**	**None**	**Intercept**	**Intercept & Trend**
Levin, Lin and Chu (LLC) panel unit root test						
Incidence of malaria	-2.75761*	-4.5567***	-2.21942	-3.7753***	-2.3153	1.3545
Climate	-1.2651	-4.2682***	-1.3191	-4.2690***	-3.1723**	-2.072**
Anaemia	2.3426	-4.929***	2.7432	-4.92936*	-2.3153	-3.0425
GDPPC	-2.7383	-5.2032***	-2.0985	-5.1811***	-6.44196***	-2.3153
Food Security	-2.2153	-5.2916***	-2.2153	-5.2913***	-8.97074***	-3.1737**
Im, Pesaran and Shin (IPS) panel unit root test						
Incidence of malaria	-	-3.3787**	-2.3113	-	-3.461891*	-2.311**
Climate	-	-5.6177	-2.183**	-	-5.6277	-1.275
Anaemia	-	-7.9941***	-2.9489	-	-8.12070***	-1.704*
GDPPC	-	-5.2916***	-2.2153	-	-5.3913***	-2.997***
Food Security	-	-5.2597	-3.873**	-	-9.8986	-3.744***
Fisher's Augmented Dickey-Fuller (ADF) panel unit root test						
Incidence of malaria	-2.3153	23.2874	21.4492	85.8820***	46.4458***	33.661**
Climate	-3.1723**	0.41108	0.57666	14.0458***	7.58982	8.057*
Anaemia	-5.291***	2.07634	1.90817	22.3840***	12.3018*	12.862*
GDPPC	-5.5497	8.15113	6.89866	63.7314***	28.6476***	24.899***
Food Security	6.66455	-2.2153	8.83831	100.640***	55.6270***	39.437***
Phillips-Perron (PP) panel unit root test						
Incidence of	-0.3489	25.1974	-5.3913***	-2.3370***	3.2203	-2.762***

malaria						
Climate	-2.9972*	0.48769	-8.8986	-2.9336	-2.9798*	-4.680
Anaemia	3.3668	0.54544	0.95209	-8.7753*	0.11921	-11.433*
GDPPC	-2.7343	8.99160	6.81063	-2.0392*	-2.3308	-5.0289*
Food Security	0.5074	13.0345	8.76036	-3.8879***	-3.1312	-4.385***

Source: Author's Computation, (2025); ***, **, * implies p-value significance at 1%, 5% and 10% respectively.

Panel unit root tests such as ADF, Phillips-Perron (PP), Im, Pesaran and Shin (IPS), Levin, Lin and Chu (LLC), and Fisher's Augmented Dickey-Fuller (ADF) tests were employed to assess the stationarity properties of the variables, which included food security, GDP per capita, Anaemia, and malaria incidence. The research demonstrates diverse results for different parameters and test criteria. Fascinatingly, the LLC test shows significant negative coefficients for both malaria incidence and climate, indicating that both variables are stationary when intercept and trend are included.

4.3. Panel Cointegration Analysis

If there is a long-term equilibrium relationship between two variables, they are cointegrated. The long-term link between the series is investigated in the research using the Kao Residual Cointegration test. The null hypothesis, that there is no cointegration among the series, is tested by examining the cointegrating relationship.

Table 2: Panel Cointegration Analysis

Pedroni Residual Cointegration Test
Series: INCID_OF_MALARIA CLIMATE FOOD__INSECURITY GDPPC P_ANEMIA

Alternative hypothesis: common AR coefs. (within-dimension)

	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	-0.271400	0.6070	-0.392133	0.6525
Panel rho-Statistic	0.118947	0.5473	0.281722	0.6109
Panel PP-Statistic	-3.966455	0.0000	-3.150165	0.0008
Panel ADF-Statistic	0.447361	0.6727	1.173202	0.8796

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	0.941068	0.8267
Group PP-Statistic	-3.608652	0.0002
Group ADF-Statistic	3.265631	0.9995

Source: Author, 2025

According to the Pedroni Residual Cointegration Test results, there are varying degrees of cointegration between the variables "INCID_OF_MALARIA" and "CLIMATE." The panels v-

Statistic and ADF-Statistic yield contradictory results, whereas the panel PP-Statistic suggests considerable cointegration. The test highlights the importance of evaluating cointegration from multiple angles to understand the relationships among variables fully.

Table 3: Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	14.027296	4	0.0072

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
CLIMATE	0.346364	-37.159180	993.390437	0.2341
P_ANEMIA	4.758998	6.235199	0.439336	0.0259
GDPPC	-0.453796	-0.899661	0.023614	0.0037
FOOD__INSECURITY	-1.513028	0.699542	0.509245	0.0019

Source: Author, 2025

To test if the random effects model is more suitable than the fixed effects model, the Correlated Random Effects - Hausman Test is used.

Test Results:

The Chi-Square statistic is 14.027296. Chi-Square d.f.The test has four degrees of freedom. Probability: The p-value for the test is 0.0072.

The test findings indicate that the fixed- and random-effects models differ statistically in a meaningful way. This shows that the random-effects model fits the data better.

Given substantial differences between the fixed and random effects for certain variables, the Hausman test generally indicates that the random-effects model is better suited to the data.

Table 4: Regression Results

Dependent Variable: INCID_OF_MALARIA
Method: Panel EGLS (Cross-section random effects)

Periods included: 13
Swamy and Arora (1972) estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLIMATE	7.70	0.56	13.74	0.00
P_ANEMIA	6.23	0.81	7.736	0.00
GDPPC	2.5	0.47	5.39	0.00
FOOD__INSECURITY	0.69	0.66	1.05	0.29
C	-179.3	58.13	-3.09	0.00

R-squared	0.68	Mean dependent var	193.98
Adjusted R-squared	0.67	S.D. dependent var	126.11
S.E. of regression	25.19	Sum squared resid	94569
F-statistic	18.75	Durbin-Watson stat	0.95
Prob(F-statistic)	0.00		

Source: Computed by the author, 2025

The statistically significant positive correlations among P_ANEMIA, GDPPC, and CLIMATE rise indicate a favourable relationship between these parameters and malaria incidence.

Food__INSECURITY's non-statistically significant coefficient indicates that it has no appreciable effect on malaria incidence.

The model incorporates estimates of component variances by Swamy and Arora (1972), as well as idiosyncratic and cross-sectional random effects.

The results suggest that variables such as GDP per capita, anaemia prevalence, and the effects of climate change should be considered when developing strategies and treatments to reduce malaria incidence. These variables have a significant impact on malaria rates. We need to put in more effort and conduct further research.

The Panel EGLS (Cross-section random effects) technique provides a comprehensive understanding of the relationship between the independent factors and the dependent variable, INCID_OF_MALARIA (malaria incidence). The findings indicate that a wide range of variables significantly affect the prevalence of malaria.

There are statistically significant positive coefficients for P_ANEMIA, GDPPC, and CLIMATE. This implies that higher GDP per capita, CLIMATE, and P_ANEMIA (Anaemia) prevalence are associated with higher malaria rates. However, there is not a statistically significant association between malaria frequency and the variable FOOD__INSECURITY. The constant component (C)'s statistically substantial negative coefficient suggests that unobserved factors negatively affecting malaria incidence are not accounted for by the model.

Based on the R-squared value, the independent variables may account for about 67.77% of the variance in malaria incidence. This demonstrates that the model and the data align well. The estimator of component variances proposed by Swamy and Arora (1972) indicates that the model may include both idiosyncratic and cross-sectional random effects.

5.0 Concluding remarks

Given that weather has a significant influence on malaria incidence, accounting for climate-related factors is crucial when developing control strategies. Reducing mosquito populations and the spread of malaria requires implementing preventive measures such as monitoring weather trends, identifying regions vulnerable to specific weather patterns, and targeting focused treatments. Health officials might coordinate control efforts with climatic trends to increase the effectiveness of preventive therapy.

The statistical significance and substantial coefficient of P_ANEMIA demonstrate the necessity for anaemia treatment. A multimodal approach that incorporates improved nutritional support, expanded healthcare access, and effective anaemia prevention and treatment programs is necessary to reduce malaria incidence. Lowering Anaemia is a key tactic for reducing the overall malaria burden.

There may be a correlation between malaria prevalence and economic development, as shown by the positive association with GDP per capita. Reducing poverty, promoting economic growth, and improving access to healthcare are among the factors that indirectly support the fight against malaria. A conducive environment for malaria management and prevention can be established by focusing on initiatives to enhance public services, educate the public, and reduce poverty.

Whole-hearted approach: Even if the variables under examination provide pertinent information in this respect, it is essential to comprehend that elements that are not visible—represented by the constant term C—influence malaria occurrence. To provide a more complete picture, future research should include other variables such as healthcare facilities, vector control strategies, and cultural norms.

One of the most crucial pieces of advice is to monitor and evaluate attempts to prevent malaria regularly. Regular data collection on the prevalence of Anaemia, the incidence of malaria, the climate, and socioeconomic characteristics makes it easier to assess programs and make decisions based on facts.

Policymakers and healthcare professionals may develop targeted strategies to reduce malaria prevalence and improve public health outcomes in affected communities by following these guidelines.

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