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Climate Change and Malaria: Impact, Vulnerability, and Adaptation Pathways in Homa Bay County, Kenya

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Abstract

This paper presents the relationship between climate change (temperature, rainfall, humidity) and incidence of malaria in Homabay County, Kenya. Climate change impacts, household exposure, sensitivity, and adaptive capacity were analysed to inform policy. The study combined ecological time-series analysis, household surveys, and key informant interviews. It analysed climate and morbidity data from 2010-2024, supplemented with primary data from 401 households and insights from 19 stakeholders. Standardized questionnaires and in-depth interviews guided data collection. The ARDL models assessed short and long-run climate effects on malaria, logistic regression examined determinants of household vulnerability, and thematic analysis generated qualitative insights. The findings showed malaria cases averaged 23,082 per month (SD = 13,402), mean temperature 23.3°C (SD = 1), rainfall 117.7 mm (SD = 67), and humidity 74%. The long-run model showed a significant baseline incidence and a highly significant first-month lag (IRR ≈ 1.92). Similarly, short-run results confirmed strong persistence, with first differenced lag significant (IRR ≈ 1.82). The household survey showed an overall moderate vulnerability to malaria (median 0.35), driven by high exposure, moderate sensitivity and adaptive capacity. Sensitivity linked to older household-head, low education, poor housing, and climate-dependent livelihoods significantly increased odds of malaria by 52%. Exposure had a positive effect on malaria incidence (OR ≈ 1.29) while stronger adaptive capacity lowered malaria risk. The study concluded that climate change has a significant impact on malaria in Homa Bay County. It highlights the need for real-time climate-health early warning systems by integrating meteorological data into IDSR for timely outbreak detection.

Keywords: *Adaptation, Climate Change, Impact, Malaria, Vulnerability.*

Introduction

Globally, climate change presents a fundamental threat to human health [1]. The health effects of climate change can arise directly from weather events like heat stress, floods, droughts, and storms, or indirectly from factors such as displacement, mental health issues, and spread of disease vectors [2]. Worldwide, an estimated 263 million malaria cases and 597,000 deaths were recorded in 2023, with 94% of the burden being in Africa. Children under five remain the most vulnerable group, representing close to 76% of malaria deaths across the continent [3]. The World Health Organization projects a further increase in annual mortalities by 250,000 between 2030 and 2050 due to extreme weather, rising disease burdens, and the global spread of vector-borne infections [4].

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In many parts of Africa, climate change threatens to undermine many of the public health gains made in the last decades [5]. Locally, Kenya faces rising health risks from climate change, including higher temperatures, heavy rainfall, and flooding, which worsen existing health challenges, particularly for vulnerable groups [6]. Evidence from the studies conducted in Kenya provide baseline relationship between climate and malaria outcomes. For example, temperature and heat in informal settlements in Nairobi [7]; and the impact of warming temperatures on malaria vector species habitat and lifecycles in coastal regions of Kenya [8].

The Homa Bay County climate change policy highlights the region's growing challenges- including declining water quality, frequent flooding, and droughts; and calls for more research on climate impacts, vulnerability, and adaptation [9]. In response, this study examined the relationship between climate factors (temperature, rainfall, and humidity) and malaria incidence, assessed household vulnerability, and identified public health adaptation measures to reduce the impact of climate change on malaria in Homa Bay County, Kenya. This paper acknowledges that human activities play a central role in causing climate change, shaping its impacts, and fostering resilience. Its findings will improve understanding of both current and future health effects of climate change and support the formulation of effective public health policies.

Materials and Methods

Study Design

This study adopted a mixed-method design that integrates quantitative and qualitative approaches to explore relationships between climate variables and malaria, population vulnerability, and local adaptation strategies.

Study Area

The study was conducted in Homa Bay County in western Kenya, a predominantly rural region situated (*Latitude 0^0 15 - $0^0$52' South: Longitudes 34^0 - 35^0 East)* along the shores of Lake Victoria. The county, with over 1.13 million people, features two main ecological zones, the lakeshore lowlands and the upland plateau, and experiences a moderate inland equatorial climate. Its economy is largely driven by agriculture and an expanding blue economy supported by extensive lake access [10]. The Figure 1 below shows the study area of Homabay County in Kenya.

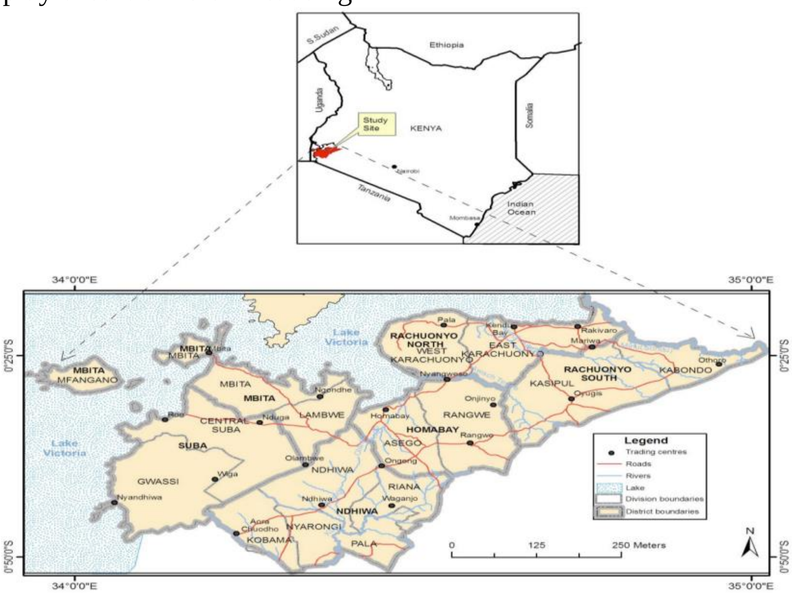

Figure 1. A map showing the study location of Homa Bay County, Kenya

Source, (Ochieng, 2017).

Study Population

The 15 years (2010-2024) secondary data for malaria illnesses were extracted from the Kenya Health Information System, while climate variables (rainfall, temperature, and humidity) were obtained from the Kenya Meteorological Department. The target population for assessing household vulnerability comprised of all 262,036 households in Homa Bay County. The head of the household served as the primary unit of analysis. Further, 19 respondents from key sectors such as health, water, agriculture, climate, and local governance volunteered as participate in the qualitative in-depth interviews.

Sample Size and Sampling Technique

All patients diagnosed with confirmed malaria in Homabay County from January 2010 to December 2024 were included in this study. Further, climate related data (temperature, rainfall and humidity) for the same 15 year-period were obtained from Kenya Meteorological Department. According to the World Meteorological Organisation, more than 10 years of data can offer predictive accuracy.

A multi-stage sampling was applied to determine the sample size for the household survey. The initial stage comprised selecting 4 sub-counties based on the ecological strata, followed by proportional allocation of households. The sample size for household survey was determined using Leslie Fischer's formula Equation 1, $n = \frac{Z^2 p(1-p)}{e^2}$ where; *n* is required sample size at 95% confidence interval, standard deviation z =1.96 with a default margin of error e =0.05.The degree of variability for the targeted households is not known, thus the study assumed the maximum variability of p = 0.5 to determine a more conservative sample size [11]. A total of 384 households were recruited as study participants, later adjusted to 422 to account for potential non-response. Systematic sampling with an interval of five households was used to select survey participants. Additionally, purposive simple random sampling was used to identify 19 key stakeholders across health, water, agriculture, climate, and local governance sectors for key informant interviews.

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Results

Secondary Data

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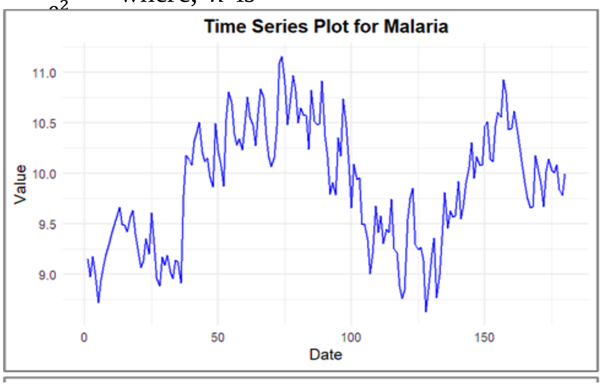
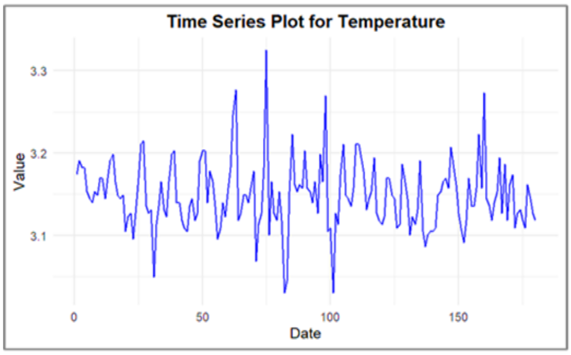


Figure



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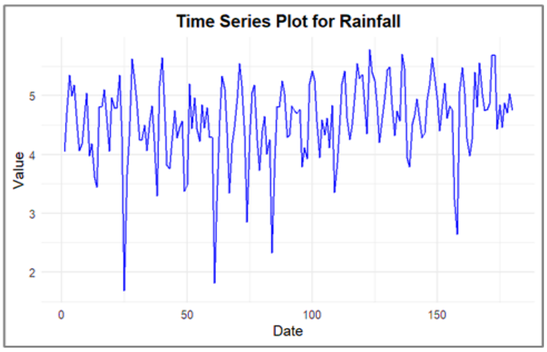

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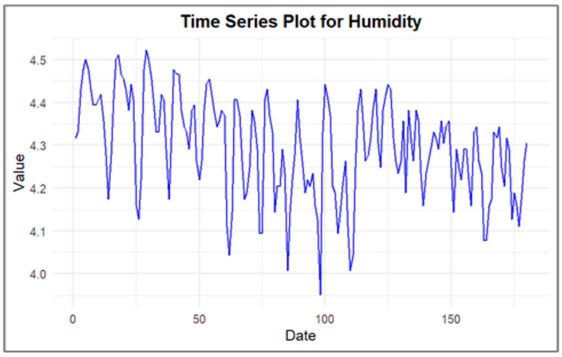

Figure

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Table

Variable	[a]Statistic	Decision	[b]Statistic	Decision
Malaria	9.573	Not	na	Not
Temperature	60.041	Detected,	2.362	Deseasonalized
Rainfall	91.361	Detected,	2.032	Deseasonalized
Humidity	58.899	Detected,	0.916	Deseasonalized

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	First			Second		
Variable	**ADF p-**	**PP pvalue**	**Decision**	**ADF p-**	**PP pvalue**	**Decision**
Malaria	0.567	0.216	NS	0.010**	0.010**	S

Temperature	0.010**	0.010**	S	0.010**	0.010**	S
Rainfall	0.010**	0.010**	S	0.010**	0.010**	S
Humidity	0.010**	0.010**	S	0.010**	0.010**	S

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Note:

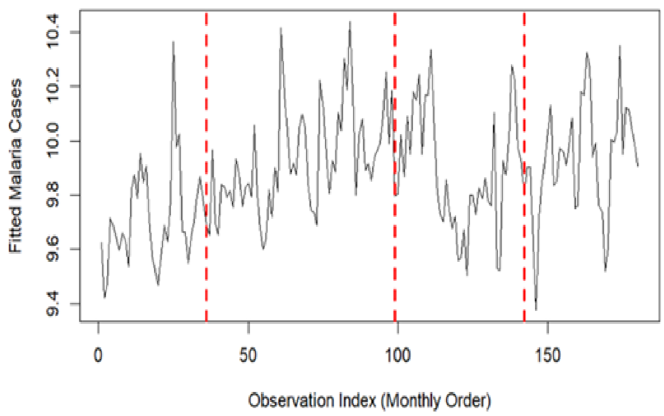
Correlation

Table

Table

	Malaria	Temperature	Rainfall	Humidity
Malaria	1.000	0.099	-	-
Temperature		1.000	-	-
Rainfall			1.000	0.439
Humidity				1.000

Structural



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Variable	Outlier(s)	Dates	Skewness	Kurtosis
Malaria	No	n/a	-	2.032
Temperature	Yes	March	0.626	5.407
Rainfall	Yes	January	-	5.755
Humidity	No	n/a	-	2.651

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Secondary

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Variable	Mean	SD	Median	IQR	Min	Max
Malaria	23,081.76	13,402.86	20,303.00	20,021.00	5,603.00	70,224.00
Temperature	23.3	1	23.2	1.1	20.7	27.8
Rainfall	117.4	67	103.2	82.7	5.4	324.5
Humidity	74	8.4	74.5	12	52	92

Results

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Coefficient	ʳEstimate	P-	IRR	VIF
Intercept	9.077	0.005**	na	na
L(Malaria,	0.652	<0.001***	1.920	6.171
L(Malaria,	-	0.154	0.925	5.801
L(Temperature,	-	0.333	0.602	1.421
L(Temperature,	-	0.035*	0.291	1.382
L(Rainfall,	-	0.596	0.974	1.731
L(Rainfall,	-	0.850	0.992	1.629
L(Humidity,	0.436	0.090†	1.546	3.550
L(Humidity,	-	0.292	0.724	3.450
Break1	0.522	<0.001***	1.686	3.685
Break2	-	<0.001***	0.639	4.258
Break3	0.355	<0.001***	1.427	2.592
R	0.847			
Adjusted	0.836			
Model	83.200	<0.001***		
Residual	1.294	0.524		
ʳSerial	17.143	0.002**		
Heteroskedasticity	11.324	0.417		
Ramsey	0.116	0.891		
Recursive	0.340	0.934		
OLS-	0.627	0.827		
Bounds	8.400	<0.001		

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Coefficient	ʳEstimate	P-	IRR	VIF
(Intercept)	0.016	0.669	na	na
L(ΔMalaria,	0.598	<0.001***	1.819	3.891
L(ΔMalaria,	-	0.222	0.930	1.070
L(ΔTemperature,	-	0.588	0.768	1.789
L(ΔTemperature,	-	0.091†	0.399	1.781

L(ΔRainfall,	-	0.949	0.997	1.620
L(ΔRainfall,	0.002	0.960	1.002	1.596
L(ΔHumidity,	0.312	0.335	1.367	1.746
L(ΔHumidity,	0.217	0.384	1.242	1.716
L(ECT,	-	<0.001***	na	3.811
Break1	-	0.900	0.994	1.240
Break2	-	0.662	0.980	1.740
Break3	0.019	0.732	1.020	1.483
R	0.232			
Adjusted	0.175			
Model	4.069	<0.001***		
Residual	1.407	0.495		
Serial	16.075	0.003**		
Heteroskedasticity	11.992	0.446		
Ramsey	1.689	0.188		
Recursive	0.979	0.040		
OLS-	0.623	0.833		

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Characteristic	**N**
Sex	
Male	198
Female	203
Age	49
Age	
Young	90
Middle-	243
Older	68
Highest	
Primary	93
Secondary	175
Tertiary/University	96
None	37
Number	5.00
Number	1.00
Number	

No	177
1–	218
3	6
Main	
Farming	158
Fishing	40
Casual	56
Business	120
Salaried	27
Malaria	
	297
	104
Sub-	
Homa	96
Rachuonyo	138
Rachuonyo	94
Suba	73
Domains	
Sensitivity	0.44
Exposure	0.63
Adaptive	0.61
Household	0.35

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Household
Overall,

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Table

Table

	Household		
Characteristic	**No,**	**Yes,**	**P-**
Sub-			0.180[a]
Homa	17	79	
Rachuonyo	38	100	
Rachuonyo	26	68	
Suba	23	50	
Sex			>0.900[a]
Male	51	147	
Female	53	150	
Age	44	52	<0.001[c]
Age			<0.001[a]
Young	35	55	
Middle-	62	181	
Older	7	61	

Highest			<0.001[a]
Primary	12	81	
Secondary	52	123	
Tertiary/University	38	58	
None	2	35	
Main			0.028[a]
Farming	34	124	
Fishing	14	26	
Casual	8	48	
Business	40	80	
Salaried	8	19	
Number			0.820[b]
No	45	132	
1–	57	161	
3	2	4	
Household			0.006[b]
>120,000	2	6	
24,000–	32	48	
<23,000	70	243	
Any			<0.001[a]
Yes	22	131	
No	82	166	
Main			<0.001[b]
Piped	5	10	
Borehole	64	96	
Surface/River/Pond	35	191	
Type			0.740[b]
Flush	0	2	
Pit	53	164	
Pit	51	130	
Open	0	1	
Primary			<0.001[b]
LPG/Electricity	5	7	
Charcoal	37	49	
Firewood	62	241	
Any			0.015[a]
Yes	6	47	
No	98	250	
Heard			0.002[a]
Yes	94	224	
No	10	73	
Climate			0.162[b]
Yes	99	291	

No	5	6	
Household			0.919[a]
Yes	53	155	
No	51	142	
Household			<0.001[a]
No	48	72	
Yes	56	225	
Area			0.003[b]
Yes	96	293	
No	8	4	
Area			>0.900[b]
Yes	104	296	
No	0	1	
Education			<0.001[a]
Secondary	2	35	
Primary	12	81	
None	90	181	
Access			0.046[a]
Yes	74	241	
No	30	56	
Any			0.466[a]
Yes	90	246	
No	14	51	
Own			0.186[a]
Yes	94	251	
No	10	46	
Household			0.002[a]
Never	13	48	
Occasionally	88	206	
Regularly	3	43	
Household			0.005[b]
Never	3	8	
Occasionally	95	235	
Regularly	6	54	
Household			0.044[a]
Yes	52	113	
No	52	184	
Any			0.004[a]
Yes	60	121	
No	44	176	
Domain			
Sensitivity	0.44	0.50	<0.001[c]
Exposure	0.50	0.63	<0.001[c]

Adaptive	0.72	0.61	0.017[c]
Household	0.12	0.46	<0.001[c]

[1]n

[a]Pearson's

Logistic

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Equation 5 results for malaria indicate that household-level climatic vulnerability significantly influences disease occurrence. Sensitivity to climatic factors was positively associated with malaria, with each unit increase in sensitivity raising the odds of reporting malaria by 1.52 times (OR = 1.52, 95% CI: 1.15-2.05, p = 0.005), while higher Exposure also increased risk (OR = 1.29, 95% CI: 1.01-1.67, p = 0.045).

Conversely, stronger Adaptive Capacity reduced the likelihood of malaria by 24% (OR = 0.76, 95% CI: 0.58-0.99, p = 0.046), highlighting the protective role of coping mechanisms. Age of the household head was another significant predictor, with middle-aged (OR = 1.76) and older adults (OR = 2.74) more likely to report malaria than younger adults. These findings underscore that high sensitivity and exposure elevate malaria risk, whereas adaptive capacity can buffer households against climatic vulnerabilities. Post-model diagnostics support the reliability and adequacy of the fitted logistic regression model

regression

Table **10**.

Table 10. Malaria Model

Predictor	**Estimate (β) (95% CI)**	**OR (95% CI)**	**P-value**
Sensitivity	0.422 (0.131, 0.713)	1.520 (1.150, 2.050)	0.005**
Exposure	0.258 (0.006, 0.510)	1.290 (1.010, 1.670)	0.045*
Adaptive capacity	-0.274 (-0.543, -0.005)	0.760 (0.580, 0.990)	0.046*
Age of Household Head			
Young Adult (18-<40 years)	-	-	-
Middle-aged Adult (41-<65 years)	0.566 (0.033, 1.099)	1.760 (1.030, 3.000)	0.037*
Older Adult (>65 years)	1.007 (0.037, 1.977)	2.740 (1.080, 7.670)	0.042*

Abbreviations: CI = Confidence Interval, OR = Odds Ratio

*Signif. codes: <0.001 '***' 0.001 '***' 0.01 '**' 0.05 '*' 0.1 '†'*

REF

Malaria Model Diagnostics

– The model recorded a null deviance of 459.05 and a residual deviance of 417.35, resulting in a reduction of approximately 41.7 points Figure 7. This reduction in deviance indicates an improvement in model fit when the predictors were included, compared to the null model containing only the intercept. The Akaike Information Criterion (AIC) for the final model was 429.35, suggesting a reasonably good fit with moderate model complexity. A lower AIC value generally reflects a better trade-off between goodness of fit and parsimony, implying that the selected model achieves an acceptable level of explanatory power without overfitting.

Variance Inflation Factor (VIF) diagnostics were used to check for multicollinearity among

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the independent variables. The generalized VIF (GVIF) values ranged from 1.09 to 1.31, corresponding to adjusted values between 1.04 and 1.15. These results fall well below the conventional threshold of 5, suggesting that multicollinearity was not a concern in the model. Therefore, the estimates for Sensitivity, Exposure, Adaptive Capacity, and Age of Household Head can be considered stable and independently meaningful.

The Hosmer-Lemeshow goodness-of-fit test further confirmed the adequacy of the model. The test yielded a Chi-square statistic of 3.42 with a p-value of 0.906, indicating that the model's predicted probabilities align well with the observed outcomes. A non-significant result ($p > 0.05$) implies that there is no evidence of lack of fit, hence the model accurately captures the observed distribution of malaria cases across households.

The McFadden pseudo-R^2 for the model was 0.091, while the ML and Cragg-Uhler (Nagelkerke) R^2 values were 0.099 and 0.145, respectively. These indicate that the model explains between 9% and 14% of the variation in the likelihood of malaria occurrence across households. Although pseudo-R^2 values are typically lower than those of linear models, these results are consistent with acceptable explanatory power in epidemiological and behavioural studies where multiple unobserved factors may influence disease outcomes.

The predictive ability of the model was further evaluated using the Receiver Operating Characteristic (ROC) curve, which yielded an Area Under the Curve (AUC) of 0.706. This suggests that the model has moderate discriminative ability, correctly distinguishing between households that reported malaria and those that did not approximately 71% of the time (Figure 6). According to standard interpretation, an AUC between 0.7 and 0.8 indicates satisfactory model performance for prediction in public health and social science contexts.

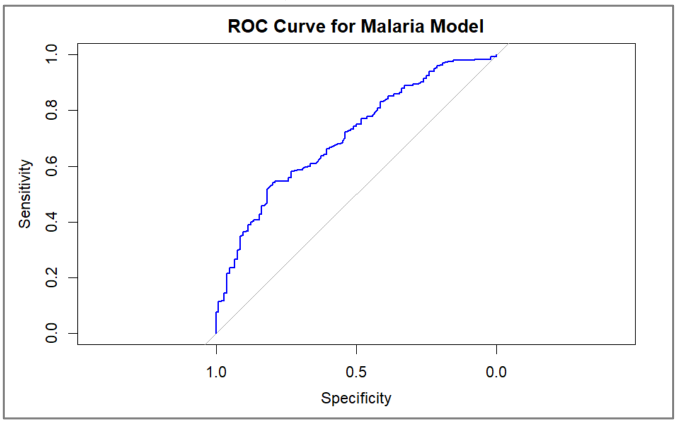

Figure 7. Malaria Model ROC Curve

Overall, the diagnostic checks confirm that the logistic regression model is statistically sound, well-fitted, and free from multicollinearity. The Hosmer-Lemeshow test indicates excellent calibration, and the AUC value suggests a moderate ability to discriminate between malaria and non-malaria households. These diagnostics collectively validate the robustness of the model and the reliability of its estimates for inferential and policy interpretation.

Discussion

Relationship Between Climate Factors and Malaria Incidence

The results of this study provide clear empirical evidence that climatic factors, particularly temperature and humidity, exert a significant influence on the incidence of malaria diseases in Homa Bay County. Using the ARDL framework, the analysis revealed both long-run and short-run relationships, with incidence rate ratios (IRRs) quantifying the magnitude of these effects. These results extend previous evidence from Kenya and Sub-Saharan Africa by identifying lag-dependent and disease-specific responses, offering actionable insights for early warning and adaptive disease control strategies.

The positive and highly significant autoregressive component of malaria incidence ($\beta = 0.652$, $p < 0.001$; IRR $\approx$ 1.92) indicates strong temporal persistence, suggesting that elevated case levels tend to carry over across months. This persistence underscores the need for continuous, rather than episodic, vector control and surveillance activities, as outbreaks are likely to sustain themselves even after climatic conditions stabilize. These findings support the argument that malaria transmission in highland and lake regions of Kenya is characterized by self-reinforcing dynamics linked to environmental and behavioural stability [12, 13].

The significant negative long-run association between temperature and malaria at a two-month lag ($\beta = -1.233$, $p = 0.035$; IRR $\approx$ 0.29) implies that sustained high temperatures may reduce mosquito survival and parasite development. This aligns with the "thermal limit hypothesis" [14, 15], suggesting that beyond certain temperature thresholds, vector reproduction and parasite incubation decline sharply. In policy terms, this has implications for spatial targeting of interventions. As warming trends continue, malaria control programs may need to shift focus from traditional hotspots to cooler, highland areas that are becoming newly suitable for transmission.

Humidity exhibited both immediate and delayed effects. The marginally positive short-term association ($\beta = 0.436$, $p = 0.090$; IRR $\approx$ 1.55) suggests that transient rises in humidity increase malaria risk, while the strong negative effect at a three-month lag ($\beta = -0.753$, $p < 0.001$; IRR $\approx$ 0.47) indicates that prolonged humid conditions eventually suppress transmission. This underscores the importance of integrating meteorological monitoring with entomological surveillance in the County Integrated Disease Surveillance and Response (IDSR) system. Predictive models that incorporate humidity thresholds could support the Ministry of Health and Kenya Meteorological Department (KMD) in issuing climate-informed vector control advisories.

The structural stability analysis for the malaria ARDL models, identified three key structural breaks, in December 2012, March 2018, and October 2021, indicating shifts in the malaria-climate relationship over time. The 2012 break, which was positive and significant (IRR = 1.686), corresponds to a period when malaria incidence increased markedly. This coincided with transitional phases in Kenya's malaria control programs, likely linked to variations in intervention coverage following the earlier *Kenya Malaria Strategy (2009-2017)*. The 2018 break, which was negative and significant (IRR = 0.639), aligns with intensified malaria prevention campaigns, including mass distribution of insecticide-treated nets (ITNs) and implementation of county-level surveillance strengthening. This structural shift suggests that public health interventions may have temporarily weakened the sensitivity of malaria transmission to climatic variations.

Conversely, the 2021 break (IRR = 1.427) reflects a resurgence in malaria incidence, coinciding with the COVID-19 pandemic period, which disrupted routine control measures, health-seeking behavior, and supply chain operations. Collectively, these breaks underscore that malaria transmission dynamics in Homa Bay County are shaped by an interaction between climate variability and episodic policy or environmental shocks. Adjusting for these breaks improved model fit and interpretability, reaffirming that malaria-climate linkages must be interpreted within the broader context of intervention intensity and health system resilience [12, 16].

Influence of Sensitivity to Climate-Related Risks on Malaria Incidence

In relation to malaria occurrence, the sensitivity domain showed a statistically significant positive association: β = 0.422 (95% CI: 0.131-0.713, p = 0.005), translating to an odds ratio (OR) of approximately 1.52 (95% CI: 1.15–2.05). This indicates that households with higher sensitivity to climatic stressors, such as older household head, lower education, poor housing and more climate-exposed livelihoods, had about 52 % higher odds of reporting malaria cases. These results align with the bivariate association findings where households with malaria had higher median sensitivity scores [0.50 (IQR 0.39-0.61) vs. 0.44 (IQR 0.33-0.50), p < 0.001]. Studies in similar African settings show that household fragility (low socioeconomic status, limited preventive capacity) amplifies vector-borne disease risk under climatic variability [17]. This finding underscores the necessity of strengthening household-level resilience, through improved housing, education, and livelihood diversification, as part of malaria control in climate-sensitive zones.

Influence of Exposure to Climate-Related Risks on Malaria Incidence

The exposure domain showed a statistically significant positive effect: β = 0.258 (95% CI: 0.006-0.510, p = 0.045), OR ≈ 1.29 (95% CI: 1.01-1.67). This suggests that households with greater direct exposure (living near stagnant water, poor drainage, flood-prone zones) experienced about 29 % higher odds of experiencing malaria. In the bivariate analysis, malaria-affected households had higher median exposure scores [0.63 (IQR 0.50-0.75) vs. 0.50 (IQR 0.25-0.75), p < 0.001], reinforcing this association. Recent empirical work confirms that exposure to vector habitats and environmental risk zones is a significant mediator of malaria transmission in coastal and lakeside African communities [18]. This outcome highlights the importance of environmental management (drainage improvement, mosquito-breeding site elimination) combined with climate-informed spatial targeting of vector control in high-exposure zones.

Influence of Adaptive Capacity on Malaria Incidence

Adaptive capacity in the model showed a statistically significant and protective effect: β = -0.274 (95% CI: -0.543 to -0.005, p = 0.046), OR ≈ 0.76 (95% CI: 0.58-0.99). This indicates that households with stronger adaptive capacity, such as diversified income, health-information access, insecticide-treated net use and early treatment options, were around 24 % less likely to experience malaria. Although bivariate exposure to malaria prevention measures was high and not significantly different between groups, the regression result reiterates the importance of measured capacity beyond mere possessions. Recent reviews emphasise that adaptation (behavioural and structural) under climate stress is central to maintaining disease resilience [19, 20]. As such, strengthening readable climate-health communication, ensuring equitable access to preventive tools, and fostering household adaptive behaviours should be integral to malaria interventions.

Equations

The following equations were applied to quantitatively assess the relationship between climate change factors and malaria occurrence within the study area. These formulas provided the analytical framework for examining how variations in temperature, rainfall, and humidity influence malaria transmission patterns over time.

Equation 1: Leslie Fischer's formula

$$n = \frac{Z^2 p(1-p)}{e^2} \tag{1}$$

Equation 2:Autoregressive Distributed Lag (ARDL) model

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=0}^{q_1} \beta_{1j} X_{1,t-j} + \sum_{j=0}^{q_2} \beta_{2j} X_{2,t-j} + \cdots + \sum_{j=0}^{q_k} \beta_{kj} X_{k,t-j} + \varepsilon_t \quad (2)$$

Equation 3: Long-run equilibrium ARDL form

$(Y_t = Y_{t-1} = Y_{t-2} = \cdots = Y^*$ and $X_{k,t} = X_{k,t-1} = \cdots = X_k^*)$:

$$Y_t = \gamma_0 + \gamma_1 X_{1,t} + \gamma_2 X_{2,t} + \cdots + \gamma_k X_{k,t} + u_t \quad (3)$$

Equation 4: Short-run equilibrium ARDL form

$$\Delta Y_t = \lambda_0 + \sum_{i=1}^{p-1} \phi_i \Delta Y_{t-i} + \sum_{j=0}^{q_1} \theta_{1j} \Delta X_{1,t-j} + \sum_{j=0}^{q_2-1} \theta_{2j} \Delta X_{2,t-j} + \cdots + \sum_{j=0}^{q_k-1} \theta_{kj} \Delta X_{k,t-j} + \psi ECT_{t-1} + \mu_t \quad (4)$$

Equation 5: General logistic regression model

$$\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \sum_{k=1}^{n} \gamma_k Z_{ik} + \varepsilon_i \quad (1)$$

Conclusion

The study concludes that climate variables, particularly temperature and humidity, play a significant role in shaping malaria incidence in Homa Bay County. Malaria showed strong temporal persistence, with temperature reducing long-term malaria risk and humidity demonstrating mixed but meaningful effects. Structural breaks aligned with major public health milestones, confirming that disease patterns emerge from the interplay between climate variability and health system interventions.

The household sensitivity substantially increases the likelihood of malaria, driven largely by age, education, housing quality, and livelihood vulnerability. Higher sensitivity elevated malaria odds, highlighting the central role of social and structural disadvantages in amplifying disease risk. This study concludes that strengthening household resilience, through improved housing, education, diversified livelihoods, is essential in mitigating climate-sensitive disease burdens. Moreover, the analysis concludes that exposure to environmental risks significantly increases malaria risk, underscoring the importance of environmental management and climate-responsive vector control.

Finally, the study concludes that stronger adaptive capacity, reflected in diversified livelihoods, access to health information, ITN use, and prompt treatment, meaningfully reduces malaria incidence, lowering the odds by about 24%. This demonstrates the importance of empowering households with preventive tools and climate-health information.

Conflict of Interest

We declare no conflict of interest.

Ethical Approval

Ethical clearance for the study was granted by the AMREF Health Africa Ethical and Scientific Review Committee (AMREF-ESRC; Approval No. P1863/2025). Authorization to conduct the research in Kenya was provided by the National Commission for Science, Technology and Innovation (NACOSTI). Written informed consent was obtained from all participants before data collection commenced.

Author Contribution

Author A: Conceptualization, Investigation, Methodology, Writing Original Draft, Formal analysis; Author B: Conceptualization, Review & editing, Supervision; Author C: Review & editing, Supervision, Project Administration

Data Availability

The data supporting the findings of this study are available on request from the authors.

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Reference

[1]. WHO, 2020, *Urgent health challenges for the next decade.* https://www.who.int/news-room/photo-story/detail/urgent-health-challenges-for-the-next-decade.

[2]. Too., S. K., Chaudhary, P., Rajwant. K., Randhawa., Gobindgarh, M., Distt, Fatehgarh, S., 2021, *Knowledge about Impact of Global Warming on Health.* https://www.researchgate.net/doi/10.13140/RG.2.2.27847.98722.

[3]. WHO, 2025, *Malaria.* https://www.who.int/news-room/fact-sheets/detail/malaria.

[4]. WHO, 2023, *Climate change.* https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health.

[5]. Coates, S., Yeshaneh, W., Davis, M., Andersen, L., 2020, The effects of climate change on human health in Africa, a dermatologic perspective: a report from the International Society of Dermatology Climate Change Committee. *Int J Dermatol.*

[6]. RCRC., 2021, Climate Change Impacts on Health and Livelihoods; *Kenya Assessment.* https://www.climatecentre.org/wp-content/uploads/RCRC_IFRC-Country-assessments-KENYA.pdf.

[7]. Scott, A. A., Misiani, H., Okoth, J., Jordan, A., Gohlke, J., Ouma G., 2017, Temperature and heat in informal settlements in Nairobi. *PLoS One*, 12(11), e0187300.

[8]. Le, P., Kumar, P., Ruiz, M., Mbogo, C., Muturi, J., 2029, Predicting the direct and indirect impacts of climate change on malaria in coastal Kenya. *PLOS One*, 6(14), e0211258.

[9]. GoK., 2021, *Homa Bay County Climate Change Policy.* https://repository.kippra.or.ke/handle/123456789/3551.

[10]. GoK., 2025, *Homa Bay County Annual Development Plan.* https://repository.kippra.or.ke/handle/123456789/5296.

[11]. Sarmah, H. K., Hazarika, B. B., 2012, Importance of the Size of Sample and Its Determination in the Context of Data Related to the Schools of Greater Guwahati. *Bulletin of the Gauhati University Mathematics Association*, 12, 55-76. https://www.scirp.org/reference/referencespapers?

[12]. Alemu, A., Lemma, B., Bekele, T., Geshere, G., Simma, E. A., Deressa, C. T., 2024, Malaria burden and associated risk factors among malaria

suspected patients attending health facilities in Kaffa zone, Southwest Ethiopia. *Malar J*, 23(1), 397.

[13]. Kipruto, E., Oluoch, O. A., Anyona, D., Mutua, E., 2017, Effect of climatic variability on malaria trends in Baringo County, Kenya. *ResearchGate*, https://www.researchgate.net/publication/317300603

[14]. Mordecai, E. A., Ryan, S. J., Caldwell, J. M., Shah, M. M., LaBeaud, A. D., 2020, Climate change could shift disease burden from malaria to arboviruses in Africa. *Lancet Planet Health*, 4(9), e416–23.

[15]. Norin, T., Malte, H., Clark, T. D., 2014, Aerobic scope does not predict the performance of a tropical eurythermal fish at elevated temperatures. *J Exp Biol*, 217(2), 244–51.

[16]. Ayanlade, A., Oluwaranti, A., Ayanlade, O. S., Borderon, M., Sterly, H., Sakdapolrak, P., 2022, Extreme climate events in sub-Saharan Africa: A call for improving agricultural technology transfer to enhance adaptive capacity. *Clim Serv*, 1(27), 100311.

[17]. Nosrat, C., Altamirano, J., Anyamba, A., Caldwell, J. M., Damoah, R., Mutuku, F., 2021, Impact of recent climate extremes on mosquito-borne disease transmission in Kenya. *PLoS Negl Trop Dis*, 15(3), e0009182.

[18]. van der Deure, T., Nogués-Bravo, D., Njotto, L. L., Stensgaard, A., 2025, Climate Change Favors African Malaria Vector Mosquitoes. *Glob Change Biol*, 31(11), e70610.

[19]. Hu, M., Zhang, D., Pei, Q., 2025, Climate change and human resilience: Behavioral and mental responses in Eurasia over the last millennium. *Prog Phys Geogr Earth Environ*, 10(49).

[20]. Lokoel, G., O’Meara, W. P., 2025, Climate change, development, and resilience: a warning from Turkana, Kenya. *Lancet Planet Health*, 9(8), 101286.