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Climate Change and Diarrhoeal Disease in Homa Bay County, Kenya: An Analysis of Impact, Vulnerability and Adaptation

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Abstract

Purpose: This study investigated the relationship between climatic factors (temperature, rainfall, humidity) and diarrhoeal disease incidence in Homa Bay County, Kenya, while assessing household exposure, sensitivity, and adaptive capacity to inform policy.

Methodology: A mixed-methods approach combined ecological time-series analysis and household surveys. Climate and morbidity data (2010-2024) were analysed alongside primary data from 401 households, collected using structured questionnaires.

Findings: Autoregressive Lag models estimated short and long-run climate effects on diarrhoeal, while logistic regression assessed household vulnerability. Mean monthly diarrhoeal cases were 4,041 (SD = 12,285), with average temperature 23.3°C (SD = 1), rainfall 117.7 mm (SD = 67), and relative humidity 74%. The long-run model indicated strong persistence, with a highly significant first lag (IRR = 1.514). Temperature showed lag-dependent effects, with early lags positive and a negative effect at the third lag. Rainfall exhibited a delayed influence, with the third lag marginally significant (IRR = 1.061), while humidity had a strong negative association at the third lag (IRR = 0.471). Short-run dynamics showed significant autoregression, with the first lag of diarrhoeal positive (IRR = 1.330). Household sensitivity, linked to older household heads, low education, poor housing, and climate-exposed livelihoods, increased diarrhoeal odds by 78%, while flood-related exposure contributed to outbreaks.

Unique Contribution to Theory, Practice and Policy: The findings of this study demonstrate that long-term variations in rainfall and humidity, when combined with structural public health interventions, play a decisive role in shaping the steady-state levels of diarrhoeal disease incidence. Consequently, effective diarrhoeal prevention strategies should prioritize reducing household sensitivity while enhancing adaptive capacity and water infrastructure, sanitation, and hygiene systems.

Keywords: *Adaptation, Climate Change, Diarrhoeal, Impact, Vulnerability*

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1. INTRODUCTION

Globally, the climate change crisis is a health crisis (WHO, 2025b). 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, air pollution, spread of disease vectors, and food and waterborne illnesses (Toor et al., 2021). The World Health Organization (WHO, 2025a) defines diarrhoea as the occurrence of three or more loose or watery stools within a 24-hour period, or a stool frequency exceeding what is normal for an individual. Each year, diarrhoeal diseases are responsible for more than 2.5 million deaths globally. According to the World Health Organization, over 80% of these deaths occur in Sub-Saharan Africa and South Asia (Troeger, et al., 2018).

Across much of Africa, health systems are under significant strain as they attempt to serve rapidly growing populations with limited resources. At the same time, climate change poses a serious risk to reversing many of the public health advances achieved in recent decades (Coates et al., 2020). At the national level, Kenya faces growing vulnerability to climate-related health risks, including rising temperatures, more intense rainfall and flooding, and increasing variability in precipitation patterns. These environmental changes are likely to worsen existing health burdens, particularly the risk of water-borne diseases and food insecurity associated with prolonged droughts, elevated land temperatures, and water scarcity. In response, Kenya's climate policies prioritize strengthening health-sector adaptation to mitigate these impacts (RCRC, 2021). Evidence from the various studies conducted in Kenya provide baseline relationship between climate and health outcomes. For example, temperature and heat in informal settlements in Nairobi (Scott et al., 2017); seasonal patterns of enteric diseases in Kenyan children (Shah et al., 2016) and the effect of climate extreme on health outcomes in Kenya (Kamuyu, 2017).

The Homa Bay County policy on climate change posits that climate change has severely affected the Lake Victoria Basin, reflected in deteriorating water quality, increasing incidences of flooding, droughts, and high health risks. It singles out the need to conduct climate change-related research on impact, vulnerability assessment, and climate change adaptation (GoK, 2021). This study therefore examined the relationship between climate change and diarrheal diseases, assessed vulnerability of human health to climate change, and established adaptation measures that reduce diarrhoeal diseases in Homabay County, Kenya. Examining how climate change affects the prevalence of diarrhoeal diseases is key to designing effective public health strategies and enhancing healthcare systems.

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2. MATERIALS AND METHODS

2.1 Study Design

This mixed-methods study integrated ecological time-series analysis and household surveys to explore associations between climate variables, transmission of diarrhoeal disease, population vulnerability, and local adaptation mechanisms.

2.2 Study Area

The research was carried out in Homa Bay County, located in western Kenya along the Lake Victoria shoreline. The county is largely rural and lies between latitudes 0°15′ and 0°52′ South and longitudes 34° and 35° East. With a population exceeding 1.13 million, Homa Bay comprises two principal ecological zones, the lakeshore lowlands and upland plateau, characterized by a moderate inland equatorial climate. Economic activities in the county are predominantly agriculture-based, complemented by a growing blue economy facilitated by extensive access to Lake Victoria (GoK, 2025). Figure 1 illustrates the geographical location of the study area within Kenya.

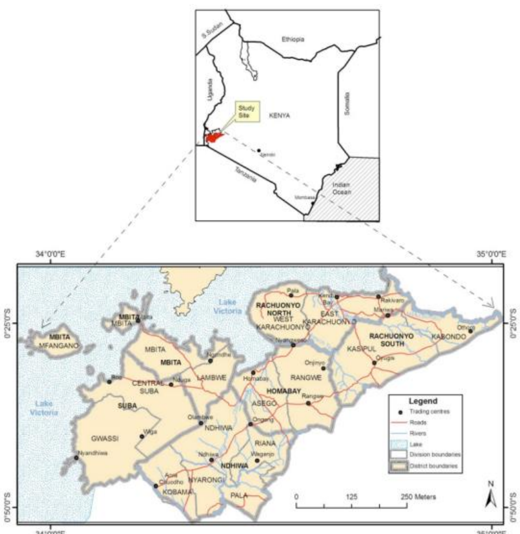

Figure 1: A map showing the study location of Homa Bay County, Kenya.

Source, *(Ochieng, 2017)**.***

2.3 Study Population

Secondary data on diarrhoeal disease morbidity covering a 15-year period (2010-2024) were sourced from the Kenya Health Information System, while climatic data, including rainfall, temperature, and humidity, were obtained from the Kenya Meteorological Department. In addition, household vulnerability assessment targeted all 262,036 households in Homa Bay County, with household heads constituting the primary unit of analysis.

2.4 Sample Size and Sampling Technique

All patients diagnosed with diarrhoeal disease 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 (*WMO*, 2025), 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 (Sarmah & Hazarika, 2012). 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.

2.5 Study Instruments and Data Collection

Climatic variables and diarrhoeal health outcomes were obtained from the Kenya Meteorological Department and the Kenya Health Information System, respectively. The climate dataset consisted of monthly records of rainfall, temperature, and humidity spanning January 2010 to December 2024, which were aligned with monthly diarrhoeal incidence data for the same timeframe. Additionally, household-level information on climate-related health vulnerability was collected using a pretested interviewer-administered questionnaire.

2.6 Pilot Study

A pilot survey was conducted with 15 households in Kisumu County, a setting with characteristics similar to Homa Bay County, to assess the reliability and validity of the questionnaire.

2.7 Statistical Analysis

The secondary data analysis combined monthly climate (rainfall, temperature, humidity) and diarrhoeal time-series data from 2010-2024. Descriptive statistics and visualizations were used to explore trends, seasonality, and anomalies. Pre-estimation diagnostics, including unit root tests, correlation checks, and multicollinearity assessments, ensured data suitability for time-series modelling. Structural break analysis identified shifts linked to climatic events or reporting changes, improving model specification and minimizing the risk of spurious regression, thereby supporting robust econometric analysis.

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The ARDL framework Equation 2 was then applied to estimate both long-run and short-run relationships between climatic factors and diarrhoeal incidence, supported by bounds testing for cointegration and an ECM for adjustment dynamics. Post estimation checks, including tests for serial correlation, heteroskedasticity, normality, and parameter stability, were undertaken to validate the reliability of model outputs. Where assumptions were violated, corrections such as Newey-West robust standard errors, additional lags, and structural break dummies were implemented.

Binary logistic regression was used to assess the influence of household vulnerability and adaptive capacity on diarrhoeal incidence, with key predictors including *Sensitivity*, *Exposure*, and *Adaptive Capacity* indices, alongside socio-demographic controls. Odds ratios quantified disease risk for each factor. Descriptive and bivariate analyses summarized household characteristics, using Chi-square or Fisher's Exact tests to select variables for multivariate models. Wilcoxon tests compared median vulnerability and adaptive capacity scores between affected and unaffected households, and spatial mapping of the Household Vulnerability Index identified geographic disparities and potential hotspots.

Pre and post-estimation diagnostics confirmed the validity of the logistic regression models, including checks for multicollinearity, influential observations, linearity, and overall fit. Goodness-of-fit measures, pseudo-R^2 values, and ROC-AUC curves indicated reliable predictive performance, with interpretable odds ratios identifying key vulnerability and adaptive capacity factors for diarrhoeal. All analyses were conducted in RStudio, with scripts and outputs documented in R Markdown to ensure transparency, reproducibility, and traceability.

3. RESULTS

3.1 Secondary Data Analysis

3.1.1 Data Management

Data checks confirmed unique records, with outliers detected in temperature, rainfall, and diarrhoeal, while humidity was stable. For the Diarrhoeal series, two outliers Table 1 were identified at indices 132 and 133, corresponding to December 2020 and January 2021. These months coincide with the height of the COVID-19 pandemic period in Kenya, during which healthcare service delivery, surveillance, and reporting mechanisms experienced major disruptions. The negative skewness (-0.494) suggests a slight bias toward higher diarrhoeal incidence in the left tail, while the kurtosis value of 4.269 (>3) indicates a leptokurtic distribution characterized by heavy tails and occasional spikes. The identified outliers may thus reflect a temporary reporting anomaly, seasonal outbreak, or environmental contamination episode, possibly linked to water supply or sanitation interruptions during the pandemic period.

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Table 1: Outlier Detection

Variable	Outlier(s) detected	Dates (in line with indices)	Skewness	Kurtosis
Diarrhoeal	Yes	December 2020, January 2021	-0.494	4.269
Temperature (°C)	Yes	March 2015, Mar 2016, April 2023	0.626	5.407
Rainfall (mm)	Yes	January 2012, January 2015, December 2016	-1.172	5.755
Humidity (%)	No	n/a	-0.386	2.651

All variables were log-transformed to stabilize variance and enable elasticity interpretation. The Figure 2, Figure 3, Figure 4, and Figure 5 below show time series plot for diarrhoeal disease and climatic factors.

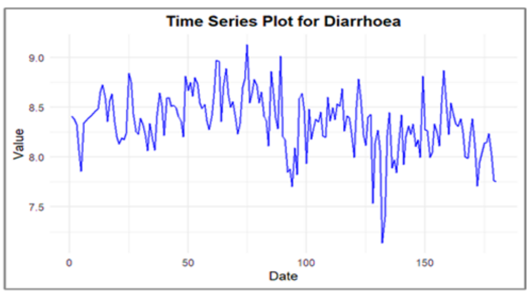

Figure 2: Time Series Plots for Diarrhoeal

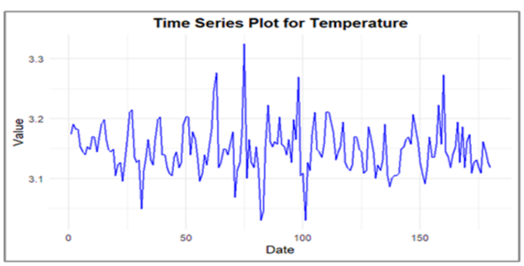

Figure 3: Time Series Plots for Temperature

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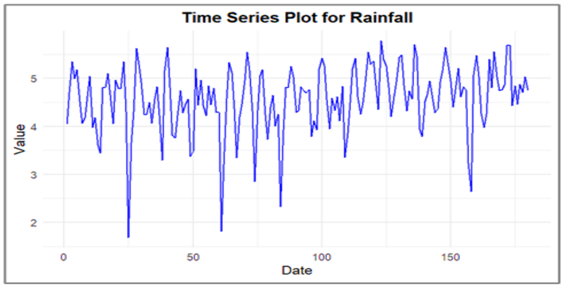

Figure 4: Time Series Plots for Rainfall

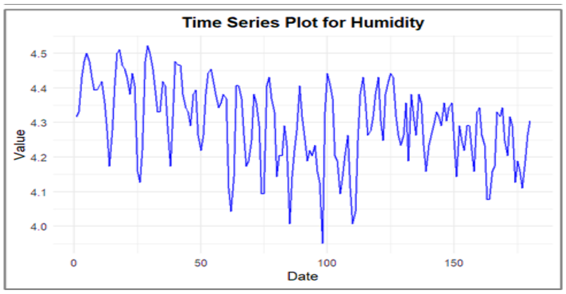

Figure 5: Time Series Plots for Humidity

Strong seasonal patterns in diarrhoeal disease, temperature, rainfall, and humidity were identified using the Kruskal-Wallis test and removed through deseasonalization, ensuring time series models reflected genuine long-run relationships Table 2.

Table 2: Seasonality Check Results

Variable	[a]Statistic (p-value)	Decision	[b]Statistic (p-value)	Decision
Diarrhoeal	49.464 (<0.001***)	Detected, Deseasonalize	1,494 (0.999)	Deseasonalized
Temperature (°C)	60.041 (<0.001***)	Detected, Deseasonalize	2.362 (0.997)	Deseasonalized
Rainfall (mm)	91.361 (<0.001***)	Detected, Deseasonalize	2.032 (0.998)	Deseasonalized
Humidity (%)	58.899 (<0.001***)	Detected, Deseasonalize	0.916 (0.999)	Deseasonalized

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

[a]*Initial check;* [b]*Post action check*

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3.1.2 Pre-Model Diagnostics

Unit root testing using both the ADF and Phillips-Perron approaches indicated Table 3 all the other variables, diarrhoeal disease, temperature, rainfall, and humidity, exhibited stationarity at level. For these variables, both ADF and PP tests was statistically significant (p=0.010), indicating rejection of the null hypothesis of a unit root at the 1% significance level. Therefore, these variables were deemed stationary at I(0) and did not require differencing.

Table 3:Stationarity Check

Variable	First Check			Second Check		
	ADF p-value	PP Pvalue	Decision	ADF p-value	PP pvalue	Decision
Diarrhoeal	0.010**	0.010**	S at I(0)	0.010**	0.010**	S at I(0)
Temperature (^oC)	0.010**	0.010**	S at I(0)	0.010**	0.010**	S at I(0)
Rainfall (mm)	0.010**	0.010**	S at I(0)	0.010**	0.010**	S at I(0)
Humidity (%)	0.010**	0.010**	S at I(0)	0.010**	0.010**	S at I(0)

*Significant codes: <0.001 '***' 0.001 '***' 0.01 '**' 0.05 '*' 0.1 '†'*

Note: Stationary = S, Not Stationary

Correlation analysis showed generally low to moderate associations among variables Table 4. Diarrhoeal disease was moderately and positively correlated with temperature (r = 0.351), indicating that higher temperatures were associated with increased diarrhoeal incidence. The correlation between diarrhoeal disease and rainfall was moderately negative (r = -0.360), suggesting that diarrhoeal incidence tended to decrease during heavy rainfall periods. The correlation between diarrhoeal disease and humidity was weakly negative (r = -0.117), indicating a negligible relationship. This suggests that humidity alone may not directly influence diarrhoeal disease dynamics, although it could act indirectly through temperature and rainfall interactions affecting water quality or bacterial persistence. Multicollinearity diagnostics using VIF indicated acceptable levels for most predictors, with temperature and rainfall lags showing minimal overlap and humidity lags exhibiting moderate collinearity (VIFs ~6-7) that remained below critical thresholds, allowing all variables to be retained.

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Table 4: Correlation Analysis

	Diarrhoeal	Temperature (ºC)	Rainfall (mm)	Humidity (%)
Diarrhoeal	1.000	0.351	-0.360	-0.117
Temperature (ºC)		1.000	-0.213	-0.404
Rainfall (mm)			1.000	0.439
Humidity (%)				1.000

Structural break analysis using the Bai-Perron test detected significant instability in diarrheal disease series ($p < 0.001$), identifying two significant breakpoints were identified at May 2017 (Break1), and November 2020 (Break2). The first breakpoint (May 2017) aligns with changes in water, sanitation, and hygiene (WASH) programming and enhanced integrated management of childhood illnesses (IMCI) strategies in Kenya, potentially improving diarrhoeal disease prevention and reporting outcomes. It also corresponds with climatic variations observed during the 2016-2017 drought period, which likely affected water safety and disease transmission. The second breakpoint (November 2020) is consistent with COVID-19 pandemic effects, which disrupted healthcare-seeking behaviours, disease reporting systems, and routine WASH service delivery. During this period, changes in population mobility and hygiene practices may have affected diarrhoeal disease trends. Figure 6 Dummy variables for these breaks were incorporated into subsequent models to control for abrupt shifts, enhance parameter stability, and reduce bias.

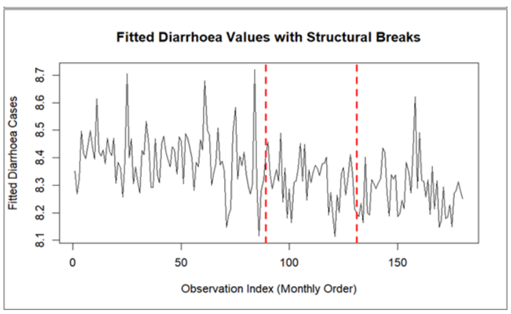

Figure 6:Structural Breaks Plot for Diarrhoeal

3.1.3 Secondary Data Descriptive Statistics

The dataset showed substantial variation in disease burden and climatic conditions across the study period Table 5.

Table 5: Secondary Data Descriptive Statistics

Variable	Mean	SD	Median	IQR	Min	Max
Diarrhoeal	4,401.46	1,285.09	4,273.50	1,514.75	1,260.00	9,194.00
Temperature (°C)	23.3	1	23.2	1.1	20.7	27.8
Rainfall (mm)	117.4	67	103.2	82.7	5.4	324.5
Humidity (%)	74	8.4	74.5	12	52	92

The mean of reported diarrhoeal cases was 4,401.5 (SD = 1,285.1), with a median of 4,273.5 and an IQR of 1,514.8. The mean temperature across the study period was 23.3 °C (SD = 1.0), with values ranging from 20.7 °C to 27.8 °C. The median temperature was 23.2 °C, and the IQR was 1.1 °C, indicating that most temperature readings were tightly clustered around the mean, reflecting generally stable thermal conditions typical of equatorial climates. The average rainfall was 117.4 mm (SD = 67.0), with a median of 103.2 mm and an IQR of 82.7 mm. The minimum recorded rainfall was 5.4 mm, while the maximum reached 324.5 mm, indicating high variability across months and years. This variability mirrors Kenya's bimodal rainfall pattern, where heavy precipitation occurs during the "long rains" (March-May) and "short rains" (October-December), and dry spells occur in between. The mean relative humidity was 74.0 % (SD = 8.4), with a median of 74.5 %, IQR = 12.0 %, and a range from 52.0 % to 92.0 %. These results indicate moderately high humidity levels throughout the study period, with some variation likely linked to rainfall cycles and temperature changes.

3.1.4 Results for Auto-Regressive Distributed Lag (ARDL) Model

3.1.4.1 The Long-Run Diarrhoeal Model

The long-run ARDL Equation 3 estimation results presented in Table 6 reveal the sustained relationships between diarrhoeal incidence and climatic factors, temperature, rainfall, and humidity, while accounting for identified structural shifts. The model's goodness-of-fit statistics show a relatively strong explanatory power, with an R^2 of 0.496 and an adjusted R^2 of 0.455, indicating that nearly 46% of the long-run variation in diarrhoeal cases is explained by the included predictors and structural components. The overall model significance ($F = 12.320$, $p < 0.001$) confirms that the collective influence of these variables is statistically significant in explaining long-term diarrhoeal disease patterns.

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Table 6: Long-Run Determinants of Diarrhoeal Incidence

Coefficient	ʳEstimate	P-value	IRR	VIF
Intercept	6.459	0.002**	na	na
L(Diarrhoeal, 1)	0.415	<0.001***	1.514	1.925
L(Diarrhoeal, 2)	-0.013	0.886	0.987	1.939
L(Temperature, 1)	0.622	0.205	1.863	1.525
L(Temperature, 2)	0.082	0.816	1.085	1.582
L(Temperature, 3)	-0.542	0.211	0.582	1.492
L(Rainfall, 1)	-0.057	0.161	0.945	1.747
L(Rainfall, 2)	-0.028	0.46	0.972	1.841
L(Rainfall, 3)	0.059	0.095†	1.061	1.732
L(Humidity, 1)	0.027	0.950	1.027	3.489
L(Humidity, 2)	0.317	0.327	1.373	5.134
L(Humidity, 3)	-0.753	<0.001***	0.471	3.406
Break1	-0.153	0.006**	0.858	2.914
Break2	-0.069	0.148	0.933	1.720
R squared	0.496			
Adjusted R squared	0.455			
Model Fit (F statistic)	12.320	<0.001***		
Residual Normality (Jarque-Bera test)	56.982	<0.001***		
ʳSerial Correlation (Breusch-Godfrey test)	8.352	0.079		
Heteroskedasticity (Breusch-Pagan test)	12.900	0.456		
Ramsey RESET test for Model Specification	1.100	0.335		
Recursive CUSUM- Parameter Stability test	1.110	0.013*		
OLS-based CUSUM (Residual Stability)- Brown-Durbin-Evans test	0.697	0.717		
Bounds F-test for Cointegration	9.079	<0.001		

*Signif. codes: <0.001 '***' 0.001 '***' 0.01 '**' 0.05 '*' 0.1 '†'*
Dependent Variable- Diarrhoeal
IRR- Incidence Rate Ratio
ʳRobust Standard Error estimates
VIF- Variance Inflation Factor

Breusch-Godfrey test for serial correlation ($p = 0.079$) indicates that autocorrelation is not a serious concern, and the Breusch-Pagan test ($p = 0.456$) rules out heteroskedasticity, suggesting consistent residual variance. The Ramsey RESET test ($p = 0.335$) further demonstrates that the model is correctly specified without evidence of omitted variable bias or nonlinearity. However, the Jarque-Bera test (JB = 56.982, $p < 0.001$) reveals a deviation from normality in the residuals, possibly due to the count-like nature of the dependent variable (diarrhoeal incidence), which often exhibits a right-skewed distribution in epidemiological data. Despite this, given the use of robust standard errors, the parameter estimates remain valid and efficient.

Stability diagnostics showed a mixed outcome: while the OLS-based CUSUM test ($p = 0.717$) indicates residual stability, the recursive CUSUM parameter stability test ($p = 0.013$) signals some degree of parameter drift, particularly around the identified breakpoints. This suggests that structural or behavioural changes in disease reporting, intervention coverage, or climatic behaviour may have slightly influenced the long-run relationships during the study period. Two structural breakpoints were incorporated into the long-run model to capture major shifts in diarrhoeal trends. Break 1 (May 2017), significant at $p = 0.006$, shows a negative coefficient ($\beta = -0.153$, IRR = 0.858), suggesting a 14% reduction in diarrhoeal incidence following this structural change. The Cointegration test, through the Bounds F-test (F-statistic = 9.079, p-value <0.001), showed a strong statistical evidence of cointegration between climatic factors and diarrhoeal incidence in the long run.

3.1.4.2 Short-Run Dynamics of Diarrhoeal Disease Incidence

The short-run ARDL model Equation 4 captures the immediate or transient adjustments in diarrhoeal incidence to changes in climatic variables and past infection levels, while controlling for structural shifts over the study period. The model explains approximately 33.7% of the short-term variation in diarrhoeal cases ($R^2 = 0.337$, Adjusted $R^2 = 0.278$), indicating moderate but meaningful explanatory power given the typically stochastic nature of epidemiological time series. The overall model fit is statistically significant ($F = 5.729$, $p < 0.001$), confirming that the combined set of variables significantly explains short-term fluctuations in diarrhoeal incidence.

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Table 7: Short-Run Dynamics of Diarrhoea Incidence

Coefficient	**[r]Estimate**	**P-value**	**IRR**	**VIF**
(Intercept)	0.009	0.669	na	na
L(ΔDiarrhoeal, 1)	0.285	0.017*	1.330	4.618
L(ΔDiarrhoeal, 2)	-0.143	0.014*	0.866	1.417
L(ΔTemperature, 1)	0.713	0.114	2.040	1.920
L(ΔTemperature, 2)	0.277	0.633	1.319	2.405
L(ΔTemperature, 3)	-0.380	0.400	0.684	1.898
L(ΔRainfall, 1)	-0.075	0.036*	0.928	1.870
L(ΔRainfall, 2)	-0.045	0.187	0.956	1.417
L(ΔRainfall, 3)	0.051	0.078†	1.053	1.943
L(ΔHumidity, 1)	0.029	0.937	1.030	1.767
L(ΔHumidity, 2)	0.379	0.116	1.461	1.831
L(ΔHumidity, 3)	-0.712	0.002**	0.491	1.833
L(ECT, 1)	-0.858	<0.001***	na	4.104
Break1	-0.015	0.684	0.986	1.570
Break2	0.003	0.956	1.003	1.561
R squared	0.337			
Adjusted R squared	0.278			
Model Fit (F statistic)	5.729	<0.001***		
Residual Normality (Jarque-Bera test)	56.836	<0.001***		
Serial Correlation (Breusch-Godfrey test)	8.184	0.085†		
Heteroskedasticity (Breusch-Pagan test)	12.853	0.538		
Ramsey RESET test for Model Specification	1.078	0.343		
Recursive CUSUM- Parameter Stability test	1.263	0.003		
OLS-based CUSUM (Residual Stability)- Brown-Durbin-Evans test	0.602	0.861		

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

Dependent Variable- Diarrhoeal

IRR- Incidence Rate Ratio

[r]Robust Standard Error estimates

VIF- Variance Inflation Factor

Diagnostic results affirm that the model is well-specified and statistically reliable. The Breusch-Godfrey test (p = 0.085) suggests no strong evidence of serial correlation in the residuals, and the Breusch-Pagan test (p = 0.538) confirms homoscedasticity, implying stable variance across observations. Similarly, the Ramsey RESET test ($p = 0.343$) indicates correct model specification, with no evidence of omitted nonlinear relationships. The Jarque-Bera test (JB = 56.836, $p < 0.001$) reveals non-normality in the residuals, possibly reflecting the skewed distribution of disease counts, a common feature in infectious disease data. The recursive CUSUM test ($p = 0.003$), however, suggests some degree of parameter instability, indicating shifts in the relationships during specific periods, likely coinciding with the identified breakpoints (May 2017 and November 2020). Despite this, the OLS-based CUSUM test ($p = 0.861$) confirms residual stability, implying that the underlying model structure remains robust overall.

Two structural breaks were incorporated to capture non-climatic changes in disease dynamics. Break 1 (May 2017) and Break 2 (November 2020) were both statistically insignificant ($p = 0.684$ and $p = 0.956$, respectively), suggesting that short-run diarrhoeal fluctuations during these periods were primarily driven by climatic and behavioural rather than structural or policy factors. The error correction term (ECT), with a coefficient of -0.858 ($p < 0.001$), is both statistically significant and of the correct (negative) sign, confirming the existence of a stable long-run equilibrium between diarrhoeal disease and its climatic determinants. The magnitude of this coefficient implies that approximately 85.8% of any short-term disequilibrium in diarrhoeal incidence is corrected within a single period (month). This high speed of adjustment underscores a rapid reversion toward the long-run equilibrium following short-run shocks, whether climatic (e.g., sudden rainfall or temperature anomalies) or structural (e.g., outbreak interventions).

3.2 Results for Household Survey

3.2.1 Socio-Demographic Characteristics and Associations

The study included 401 households from across Homa Bay County. Household heads were almost evenly split by gender, with women accounting for 51% and men 49%, and the mean age was 51 years (SD = 13), with the majority (61%) falling within the middle-aged category Table 8. Educational attainment was generally moderate to high, as 44% of respondents had completed secondary education and 24% had attained tertiary-level training. The mean household size was 5.2 individuals (SD = 2.5), and most households reported having no more than one child under the age of five. Livelihoods were largely centred on farming (39%) and small-scale business activities (30%), indicating substantial reliance on climate-sensitive sources of income.

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Table 8: Socio-Demographic Characteristics

Characteristic	N = 401[1]
Sex of household head	
Male	198 (49%)
Female	203 (51%)
Age of household head (years)	49 (40, 60)
Age of household head categorized (years)	
Young Adult	90 (22%)
Middle-aged Adult	243 (61%)
Older Adult	68 (17%)
Highest Level of Education Attained	
Primary	93 (23%)
Secondary	175 (44%)
Tertiary/University	96 (24%)
None	37 (9.2%)
Number of Household Members	5.00 (4.00, 6.00)
Number of Children Under 5 years	1.00 (0.00, 1.00)
Number of Children Under 5 years Categorized	
No child under 5	177 (44%)
1–2 children	218 (54%)
3 or more children	6 (1.5%)
Main source of livelihood	
Farming	158 (39%)
Fishing	40 (10.0%)
Casual Labor/Other	56 (14%)
Business	120 (30%)
Salaried	27 (6.7%)
Diarrhoeal Cases in Last Six Months	
Yes	153 (38%)
No	248 (62%)
Sub-County	
Homa Bay Town	96 (24%)
Rachuonyo North	138 (34%)
Rachuonyo South	94 (23%)
Suba South	73 (18%)
Domains	
Sensitivity	0.44 (0.39, 0.56)
Exposure	0.63 (0.50, 0.75)
Adaptive Capacity	0.61 (0.50, 0.78)
Household Vulnerability Index	0.35 (0.15, 0.60)

[1]*n (%); Median (Q1, Q3)*

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Respondents were geographically distributed across the county's sub-counties, with the highest representation from Rachuonyo North (34%) and Homa Bay Town (24%). Household Vulnerability Index (HVI) analysis revealed moderate sensitivity (median = 0.44), high exposure (median = 0.63), and moderate adaptive capacity (median = 0.61). These components yielded an overall HVI median score of 0.35, signifying a moderate level of vulnerability to climate-related health risks Table 8.

3.2.2 Household Reported Diarrheal Disease in the Last Six Months

Overall, diarrhoeal cases were reported in 38% (n = 153) of the households in the past six months. The distribution of diarrhoeal illness varied across several household and socio-demographic factors. Although differences by sub-county were not statistically significant (*p = 0.150*), Rachuonyo North recorded the highest proportion of diarrhoeal cases (28%), followed by Rachuonyo South (28%) and Homa Bay Town (25%). Table 9 below provides the details.

Table 9: Association of Diarrhoeal Incidence and Household Characteristics

Characteristic	**No,** N = 248[1]	**Yes,** N = 153[1]	**P-value**
Sub-County			0.150[a]
Homa Bay Town	58 (23%)	38 (25%)	
Rachuonyo North	95 (38%)	43 (28%)	
Rachuonyo South	51 (21%)	43 (28%)	
Suba South	44 (18%)	29 (19%)	
Sex of household head			0.688[a]
Male	120 (48%)	78 (51%)	
Female	128 (52%)	75 (49%)	
Age of household head (years)	47 (39, 58)	52 (44, 62)	0.001[c]
Age of household head categorized (years)			0.009[a]
Young Adult	68 (27%)	22 (14%)	
Middle-aged Adult	139 (56%)	104 (68%)	
Older Adult	41 (17%)	27 (18%)	
Highest education level attained			<0.001[b]
Primary	44 (18%)	49 (32%)	
Secondary	106 (43%)	69 (45%)	
Tertiary/University	75 (30%)	21 (14%)	
None	23 (9.3%)	14 (9.2%)	
Main source of livelihood			<0.001[a]
Farming	92 (37%)	66 (43%)	
Fishing	16 (6.5%)	24 (16%)	
Casual Labor/Other	32 (13%)	24 (16%)	
Business	84 (34%)	36 (24%)	
Salaried	24 (9.7%)	3 (2.0%)	
Number of children under 5 years categorized			0.743[b]

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Characteristic	**No,** N = 248[1]	**Yes,** N = 153[1]	**P-value**
No child under 5	113 (46%)	64 (42%)	
1–2 children	131 (53%)	87 (57%)	
3 or more children	4 (1.6%)	2 (1.3%)	
Household monthly income			0.038[b]
>120,000	7 (2.8%)	1 (0.7%)	
24,000–120,000	57 (23%)	23 (15%)	
<23,000	184 (74%)	129 (84%)	
Any household member with chronic illness?			0.019[a]
Yes	83 (33.5%)	70 (45.8%)	
No	165 (66.5%)	83 (54.2%)	
Main source of drinking water			0.245[a]
Piped	11 (4.4%)	4 (2.6%)	
Borehole	105 (42%)	55 (36%)	
Surface/River/Pond	132 (53%)	94 (61%)	
Type of toilet facility			0.009[c]
Flush	2 (0.8%)	0 (0%)	
Pit latrine with slab	147 (59%)	70 (46%)	
Pit latrine without slab	98 (40%)	83 (54%)	
Open defecation	1 (0.4%)	0 (0%)	
Primary cooking fuel			0.002[b]
LPG/Electricity	11 (4.4%)	1 (0.7%)	
Charcoal	63 (25%)	23 (15%)	
Firewood	174 (70%)	129 (84%)	
Any child diagnosed with malnutrition in the last year?			<0.001[a]
Yes	16 (6.5%)	37 (24.2%)	
No	232 (93.5%)	116 (75.8%)	
Heard of climate change			0.025[a]
Yes	206 (83.1%)	112 (73.2%)	
No	42 (16.9%)	41 (26.8%)	
Climate change issue important to household			0.008[b]
Yes	237 (95.6%)	153 (100%)	
No	11 (4.4%)	0 (0%)	
Household located in flood-prone area			0.207[a]
Yes	122 (49.2%)	86 (56.2%)	
No	126 (50.8%)	67 (43.8%)	
Household located near stagnant water bodies			0.873[a]
Yes	175 (70.6%)	106 (69.3%)	
No	73 (29.4%)	47 (30.7%)	

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Characteristic	**No,** N = 248[1]	**Yes,** N = 153[1]	**P-value**
Area experienced unusual rainfall changes (past 12 months)			0.004[b]
Yes	236 (95.2%)	153 (100%)	
No	12 (4.8%)	0 (0%)	
Area experienced extreme temperatures (past 12 months)			0.382[b]
Yes	248 (100%)	152 (99.3%)	
No	0 (0%)	1 (0.7%)	
Education level of household head (recoded)			0.004[a]
Secondary and above	23 (9.3%)	14 (9.2%)	
Primary	44 (18%)	49 (32%)	
None	181 (73%)	90 (59%)	
Access to health facility within 5 km			0.240[a]
Yes	200 (80.6%)	115 (75.2%)	
No	48 (19.4%)	38 (24.8%)	
Any adult in household insured (SHA/private)			0.004[a]
Yes	197 (79.4%)	139 (90.8%)	
No	51 (20.6%)	14 (9.2%)	
Own at least one mosquito net per two people			0.353[a]
Yes	217 (87.5%)	128 (83.7%)	
No	31 (12.5%)	25 (16.3%)	
Household treats drinking water			0.122[a]
Never	20 (8.1%)	10 (6.5%)	
Sometimes	185 (75%)	127 (83%)	
Always	43 (17%)	16 (10%)	
Household receives weather information			0.177[a]
Never	33 (13%)	28 (18%)	
Occasionally	182 (73%)	112 (73%)	
Regularly	33 (13%)	13 (8.5%)	
Household receives health information			0.003[b]
Never	5 (2.0%)	6 (3.9%)	
Occasionally	195 (79%)	135 (88%)	
Regularly	48 (19%)	12 (7.8%)	
Household involved in social safety net			0.595[a]
Yes	99 (39.9%)	66 (43.1%)	
No	149 (60.1%)	87 (56.9%)	
Any household member received health education on climate-related diseases			0.251[a]
Yes	118 (47.6%)	63 (41.2%)	

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Characteristic	**No,** N = 248[1]	**Yes,** N = 153[1]	P-value
No	130 (52.4%)	90 (58.8%)	
Domain Scores			
Sensitivity	0.44 (0.39, 0.56)	0.50 (0.44, 0.61)	<0.001[c]
Exposure	0.63 (0.50, 0.75)	0.63 (0.50, 0.75)	0.200[c]
Adaptive Capacity	0.61 (0.50, 0.78)	0.61 (0.50, 0.72)	0.130[c]
Household Vulnerability Index	0.22 (0.07, 0.49)	0.54 (0.35, 0.77)	<0.001[c]

[1]n (%); Median (Q1, Q3)
[a]Pearson's Chi-squared test; [b]Fisher's exact test; [c]Wilcoxon rank sum test

3.2.3 Logistic Regression Results

The logistic regression model Equation 5 examined the relationship between diarrhoeal occurrence within the last six months and household-level climatic vulnerability domains, specifically, *sensitivity*, *exposure*, and *adaptive capacity*, while adjusting for age category of the household head and the main source of livelihood. Results in Table 10 show that sensitivity to climatic factors was a statistically significant predictor of diarrhoeal occurrence in households ($\beta = 0.578$, 95% CI: 0.289-0.866, $p < 0.001$). The corresponding odds ratio (OR = 1.78, 95% CI: 1.34-2.39) indicates that for every one-unit increase in household sensitivity to climatic conditions, the odds of reporting diarrhoeal increased by approximately 78%. This finding suggests that households more vulnerable to changes in temperature, rainfall, or humidity, such as those with poor sanitation, inadequate water access, or limited infrastructure, are more likely to experience diarrhoea episodes.

Table 10: Diarrhoeal Model

Predictor	Estimate (β) (95% CI)	OR (95% CI)	P-value
Sensitivity	0.578 (0.289, 0.866)	1.78 (1.34, 2.39)	<0.001***
Exposure	-0.051 (-0.284, 0.182)	0.95 (0.75, 1.20)	0.670
Adaptive capacity	-0.068 (-0.299, 0.163)	0.93 (0.74, 1.18)	0.567
Age of Household Head			
Young Adult (18-<40 years)	-	-	-
Middle-aged Adult (41-<65 years)	0.847 (0.259, 1.435)	2.33 (1.31, 4.27)	0.005**
Older Adult (>65 years)	0.045 (-0.741, 0.831)	1.05 (0.48, 2.30)	0.911
Main Source of Livelihood			
Farming	-	-	-
Fishing	1.004 (0.239, 1.768)	2.73 (1.28, 5.96)	0.010**
Casual Labor/Other	0.041 (-0.619, 0.701)	1.04 (0.54, 2.01)	0.903
Business	-0.116 (-0.663, 0.431)	0.89 (0.51, 1.54)	0.679
Salaried	-0.882 (-2.211, 0.447)	0.41 (0.09, 1.40)	0.193

Abbreviations: CI = Confidence Interval, OR = Odds Ratio
*Signif. codes: <0.001 '***' 0.001 '***' 0.01 '**' 0.05 '*' 0.1 '†'*

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In contrast, exposure and adaptive capacity were not statistically significant predictors of diarrhoeal disease. The effect of exposure (β = -0.051, 95% CI: -0.284-0.182, OR = 0.95, p = 0.670) implies no substantial difference in diarrhoeal risk based on the degree of climatic exposure. Similarly, adaptive capacity (β = -0.068, 95% CI: -0.299-0.163, OR = 0.93, p = 0.567) showed a modest but non-significant negative association, suggesting that differences in coping ability, such as access to health services or social support systems, did not significantly alter the likelihood of diarrhoeal occurrence in this dataset.

Among the control variables, the age of the household head was a significant factor. Households headed by middle-aged adults (41-64 years) had more than twice the odds of reporting diarrhoeal disease compared to those led by young adults (β = 0.847, 95% CI: 0.259-1.435, OR = 2.33, p = 0.005). This could reflect differences in household composition, caregiving roles, or exposure to environmental health risks across age groups. Conversely, households with older heads (>65 years) did not show significant differences (OR = 1.05, p = 0.911).

Regarding livelihood sources, households that depended primarily on fishing were significantly more likely to report diarrhoeal cases than those relying on farming (β = 1.004, 95% CI: 0.239-1.768, OR = 2.73, p = 0.010). This association may be attributed to the proximity of fishing communities to open water bodies, which may serve as both livelihood sources and contamination points, thereby increasing waterborne infection risks. Other livelihood categories, including casual labour, business, and salaried employment, showed no statistically significant associations with diarrhoeal occurrence ($p > 0.05$).

3.2.4 Diarrhoeal Model Diagnostics

The diagnostics results for the diarrhoeal disease model indicate an overall acceptable model fit and validity of the logistic regression assumptions. The model yielded a null deviance of 533.18 on 400 degrees of freedom and a residual deviance of 485.36 on 391 degrees of freedom, suggesting that the inclusion of predictor variables improved the model compared to the null (intercept-only) model. The corresponding Akaike Information Criterion (AIC) value of 505.36 reflects a relatively good balance between model complexity and explanatory power. The Variance Inflation Factor (VIF) values were all below the conventional threshold of 5, indicating no major concerns regarding multicollinearity among the predictor variables. The generalized VIF values ranged between 1.04 and 1.25, implying that the predictors contributed unique information to the model without inflating standard errors.

The Hosmer-Lemeshow goodness-of-fit test produced a statistic of 11.716 with 8 degrees of freedom and a p-value of 0.1643. Since the p-value exceeds 0.05, the null hypothesis that the model fits the data adequately cannot be rejected, implying that the model provides a good fit between observed and predicted probabilities of diarrhoeal occurrence. Model explanatory power was assessed using several pseudo-R^2 measures. The McFadden R^2 was 0.0897, while the r^2ML and

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r^2CU values were 0.112 and 0.153, respectively. These values are typical for cross-sectional health data, indicating a moderate explanatory capacity of the model.

Finally, the Area Under the Receiver Operating Characteristic (ROC) Curve (AUC) was 0.7023 Figure 7, suggesting that the model has acceptable discriminatory ability. This means the fitted model correctly distinguishes between cases and non-cases of diarrhoeal disease about 70% of the time, which is statistically satisfactory for public health applications. Overall, the diagnostics confirm that the diarrhoeal model is statistically sound, with no evidence of multicollinearity, an adequate fit to the data, and a moderate-to-good ability to classify outcomes.

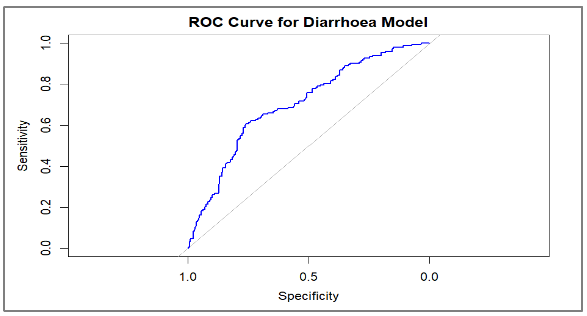

Figure 7: Diarrhoea Model ROC Curve

4. DISCUSSION

4.1 Relationship between Climate Factors and Disease 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 diarrhoeal diseases in Homa Bay County. Using the ARDL framework, the analysis revealed both short-run and long-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 lagged dependent variables demonstrate strong persistence in diarrhoeal cases. The first lag (L_1 Diarrhoeal, $\beta = 0.415$, $p < 0.001$) is positive and highly significant, implying that a 1% increase in diarrhoea incidence in the previous period leads to approximately a 51% increase in the current incidence rate (IRR = 1.514). This persistence reflects the chronic and cyclical nature of diarrhoeal disease patterns, where unaddressed environmental contamination, inadequate sanitation, and continuous pathogen exposure sustain infection levels over time. The second lag ($\beta = -0.013$, $p = 0.886$) is statistically insignificant, suggesting that the persistence effect does not extend beyond one lag in the long run. Similarly, temperature emerges as an important but nonlinear driver of diarrhoeal incidence. The first lag of temperature ($p = 0.114$) indicate that a rise in temperature is associated with a twofold increase (IRR = 2.04) in diarrhoeal incidence within a one-month lag. This suggests that short-term warming may enhance

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bacterial growth, food spoilage, and water contamination. The second lag ($\beta = 0.277$, $p = 0.633$) and third lag ($\beta = -0.380$, $p = 0.400$) are statistically insignificant, but the sign reversal hints at a delayed cooling effect, where sustained high temperatures may ultimately reduce water stagnation and pathogen survival.

Further, rainfall shows more consistent and interpretable long-run effects. Both the first ($\beta = -0.057$, $p = 0.161$) and second ($\beta = -0.028$, $p = 0.460$) lags have negative but insignificant coefficients, implying that light or early rainfall events may have a limited immediate role in disease persistence, perhaps due to partial flushing of contaminants. The third lag ($\beta = 0.059$, $p = 0.095$†) is positive and marginally significant, suggesting that cumulative or lagged rainfall increases diarrhoeal incidence by approximately 6% (IRR = 1.061) after a delay of about three months. Humidity exerts mixed but significant long-run effects. While the first ($\beta = 0.027$, $p = 0.950$) and second ($\beta = 0.317$, $p = 0.327$) lags are positive but insignificant, suggesting minimal long-term amplification effects, the third lag ($\beta = -0.753$, $p < 0.001$) is strongly negative and statistically significant, indicating that sustained high humidity over longer periods is associated with a 53% reduction in diarrhoeal incidence (IRR = 0.471). These finding is consistent with Armando et al. (2024) and Deshpande et al., (2020), who found that delayed post-rainfall peaks in diarrhoeal incidence often follow disruptions in sanitation infrastructure.

Similarly, the diarrhoeal disease ARDL models revealed two structural breaks, May 2017 and November 2020, reflecting major inflection points in the climate–disease relationship. The 2017 break, which showed a significant negative effect (IRR = 0.858), corresponds with the scaling up of *Water, Sanitation, and Hygiene (WASH)* initiatives and health system reforms under the *Kenya Health Policy (2014–2030)* and devolution of health services. These interventions likely improved sanitation coverage and safe water access, thereby reducing vulnerability to diarrhoeal disease and diminishing the long-run sensitivity of diarrhoeal incidence to climatic fluctuations. The 2020 break, though statistically insignificant, coincides with the COVID-19 pandemic, during which heightened hygiene practices and restricted movement may have temporarily altered exposure and reporting patterns. However, these disruptions appear short-lived, as long-run equilibrium relationships between diarrhoeal disease and climatic factors (particularly humidity and temperature) remained stable post-adjustment. Accounting for these structural breaks not only enhanced model stability but also emphasized the role of public health interventions and systemic disruptions in modulating climate-disease dynamics. These findings reinforce recent evidence (Armando, 2024) that climate-sensitive diseases must be analysed within the context of policy transitions and health emergencies that temporarily distort exposure and transmission pathways.

4.2 Influence of Sensitivity to Climate-Related Risks on diarrhoeal Incidence

For diarrhoeal disease, sensitivity emerged as a strong predictor: $\beta = 0.578$ (95% CI: 0.289-0.866, $p < 0.001$), OR ≈ 1.78 (95% CI: 1.34-2.39). Thus, each unit increase in household sensitivity raised the odds of reported diarrhoea by approximately 78%. The age of the household head was significantly associated with diarrhoeal illness (*p = 0.001*). Households with older heads (median age = 52 years; IQR: 44-62) reported a higher prevalence of diarrhoeal disease compared to those led by younger adults (median age = 47 years; IQR: 39-58). When categorized, diarrhoeal cases were more common among middle-aged adults (68%) compared to young adults (14%) and older adults (18%) (*p = 0.009*). The educational attainment of household heads also demonstrated a significant association (*p < 0.001*). Households headed by individuals with only primary education (32%) or no formal education (9%) were more likely to report diarrhoea compared to those with secondary (45%) or tertiary education (14%). This finding implies that lower education levels may limit awareness and adoption of safe water, sanitation, and hygiene (WASH) practices, thereby increasing vulnerability to diarrhoeal diseases.

Household economic status and livelihood type were key determinants of diarrhoeal disease occurrence. Households with monthly incomes below KES 23,000 experienced significantly higher rates of diarrhoea (84%) compared to those earning above KES 24,000 (16%; *p = 0.038*). Similarly, the main source of livelihood showed a strong association (*p < 0.001*), where farming (43%) and casual labour (16%) were predominant among affected households, while those engaged in salaried employment (2%) or business (24%) reported fewer cases. These findings highlight the role of economic vulnerability in shaping exposure and sensitivity to sanitation-related diseases, potentially mediated by differences in water access, housing, and nutrition. Notably, environmental and sanitation conditions emerged as strong correlates of diarrhoeal occurrence. The type of toilet facility used by households was significantly associated with diarrhoea (*p = 0.009*). Households using pit latrines without slabs (54%) experienced a higher burden compared to those with pit latrines with slabs (46%), while cases were rare among households with flush toilets (0%). Likewise, primary cooking fuel showed a notable relationship (*p = 0.002*), with firewood users (84%) reporting more diarrhoea than those using charcoal (15%) or clean fuels such as LPG or electricity (0.7%). These findings suggest that poorer households relying on traditional fuels and inadequate sanitation are disproportionately affected.

These patterns resonate with recent literature emphasising the role of WASH-related vulnerabilities (poor sanitation, unsafe water access, nutritional deficits) in driving diarrhoeal disease under climate stress (Marcus et al., 2023);(Mbaka & Vieira, 2022). Policy implications point to integrating climate vulnerability assessments into WASH and early-warning programs, targeting households with higher sensitivity to reduce diarrhoeal disease burden in changing climate contexts.

4.3 Influence of Exposure to Climate-Related Risks on Diarrhoeal Incidence

The diarrhoeal model's exposure domain was not statistically significant: $\beta = -0.051$ (95% CI: -0.284-0.182, $p = 0.670$), OR $\approx$ 0.95. In bivariate comparison, exposure scores did not differ significantly between affected and unaffected households ($p > 0.20$). This suggests that household exposure to climate hazards (as measured) does not independently predict diarrhoeal incidence once sensitivity and other controls are considered. Climate awareness and perceptions of environmental changes also showed meaningful associations. Households that had heard of climate change were less likely to report diarrhoea (73%) than those that had not (27%) ($p = 0.025$), underscoring the importance of information access in mitigating climate-sensitive health outcomes. Similarly, those that considered climate change an important household issue were exclusively within the diarrhoea-affected group ($p = 0.008$), perhaps reflecting post-exposure awareness. Notably, all diarrhoea-affected households reported experiencing unusual rainfall patterns in the previous 12 months (100%), compared to 95% among unaffected households ($p = 0.004$). This suggests that changes in rainfall patterns, which may increase contamination of surface and groundwater, play a critical role in diarrhoea transmission.

Literature in the climate-waterborne disease domain suggests that exposure pathways may be complex and mediated by sanitation behaviour rather than simple proximity metrics (Shanono, 2023). The policy takeaway is that for diarrhoea risk reduction, emphasis may better be placed on reducing household sensitivity (and strengthening adaptive capacity) rather than solely focusing on exposure reduction.

4.4 Influence of Adaptive Capacity on Disease Incidence

There was no statistically significant influence of adaptive capacity on household diarrhoeal disease occurrence, $\beta = -0.068$ (95% CI: -0.299-0.163, $p = 0.567$), OR ≈ 0.93. This suggests that measured adaptive capacity did not independently reduce diarrhoeal odds in this sample. Adjusted effect was modest, and bivariate comparisons revealed limited differences across capacity levels. For instance, households with health insurance coverage were significantly more represented among those reporting diarrhoea (91%) than among those without (79%) ($p = 0.004$). This could indicate a greater likelihood of illness detection or health-seeking behaviour among insured households. Access to health facilities within 5 km was not statistically significant ($p = 0.240$), though the trend suggested somewhat higher diarrhoeal prevalence among those living farther from health centers. Further, receiving health information was strongly associated with diarrhoeal status ($p = 0.003$). Households that only occasionally received health information (88%) were more likely to report diarrhoea than those who received it regularly (8%). This underscores the importance of consistent, community-based health communication in preventing diarrhoeal disease outbreaks.

This may reflect that adaptive capacity as operationalised does not fully capture sanitation behaviour or communal support systems relevant to diarrhoeal risk. Other recent work has also found inconsistent adaptive capacity effects for water-borne disease in low-income settings (Chan et al., 2021). While adaptation remains conceptually important, programme design for diarrhoeal

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disease must more deeply address infrastructure, sanitation service access and communal water systems rather than only individual household capacity.

4.5 Equations

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

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

Equation 3: Long-run equilibrium ARDL form

$$\begin{gathered}(Y_t = Y_{t-1} = Y_{t-2} = \cdots = Y^* \text{ and } X_{k,t} = X_{k,t-1} = \cdots = X_k^*): \\ Y_t = \gamma_0 + \gamma_1 X_{1,t} + \gamma_2 X_{2,t} + \cdots + \gamma_k X_{k,t} + u_t\end{gathered} \tag{3}$$

Equation 4: Short-run equilibrium ARDL form

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

Equation 5: General logistic regression model

$$\left(\frac{P_i}{1 - P_i}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \sum_{k=1}^{n} \gamma_k Z_{ik} + \varepsilon_i \tag{5}$$

5. UNIQUE CONTRIBUTION TO THEORY, PRACTICE AND POLICY

Future studies should expand climate–health research to other climate-sensitive diseases and regions using mixed-methods and multi-level approaches. Comparative, longitudinal, and participatory designs are needed to capture spatial variation, behavioural influences, and changes in adaptive capacity over time. Incorporating advanced analytical methods such as Bayesian and machine-learning models could further improve causal understanding and address uncertainty in climate-disease relationships.

This study contributes to public health practice by demonstrating the need to shift diarrhoeal disease prevention from individual-level adaptation toward strengthened community infrastructure. It underscores the importance of improving water and sanitation systems, sustaining hygiene promotion, and institutionalizing robust climate-health surveillance and feedback mechanisms to guide timely, evidence-based program adjustments.

The Ministry of Health and the Kenya Meteorological Department should integrate real-time climate data into disease surveillance systems to support early warning and proactive responses to malaria and diarrhoeal outbreaks. At the county level, embedding climate–disease risk mapping and vulnerability assessments into development and health planning frameworks would promote risk-informed investments aligned with national health and climate policies.

6. CONCLUSION

The findings of this study demonstrate that long-term variations in rainfall and humidity, when combined with structural public health interventions, play a decisive role in shaping the steady-state levels of diarrhoeal disease incidence. Overall, the results affirm that diarrhoeal illnesses are highly sensitive to climatic conditions and that strengthening household resilience, particularly through health education and improved economic stability, is essential for reducing disease risk. Moreover, the study reveals that vulnerability and behavioural determinants exert a greater influence on diarrhoeal outcomes than environmental exposure alone. Consequently, effective diarrhoea prevention strategies should prioritize reducing household sensitivity while enhancing adaptive capacity and water, sanitation, and hygiene systems. Ultimately, the evidence underscores the need to focus prevention efforts on systemic improvements in water supply, sanitation infrastructure, and health service delivery, rather than relying solely on household-level adaptive responses.

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.

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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