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Volatility Dynamics of Climate-Driven Health Risks: Applications of Garch Family Models

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Abstract

Climate change has emerged as one of the most pressing global challenges, with significant implications for human health. Variations in temperature, rainfall, and extreme weather events are increasingly linked to outbreaks of vector-borne diseases, respiratory illnesses, and heat-related morbidity. While prior research has primarily focused on linear relationships between climate and health outcomes, limited attention has been given to the volatility dynamics underlying these interactions. This study addresses this gap by applying the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models to investigate the persistence, clustering, and asymmetry of climate-induced health risks in Nigeria. Monthly climate data (temperature anomalies and rainfall deviations) were obtained from the Nigerian Meteorological Agency (NIMET) and the Climate Research Unit (CRU), while health data (malaria and respiratory infections) were sourced from the Nigerian Centre for Disease Control (NCDC), covering the period January 2000 to December 2022. Following logarithmic transformation of health outcomes to stabilize variance, GARCH (1,1), EGARCH (1,1), and TGARCH (1,1) models were estimated. The findings indicate strong volatility persistence in malaria incidence driven by rainfall anomalies, alongside asymmetric effects in respiratory infections associated with temperature shocks. Volatility clustering was evident in both diseases, highlighting the nonlinear and unpredictable nature of climate–health interactions. This study contributes to the literature by moving beyond correlation-based frameworks and introducing volatility modeling to the climate–health nexus. The results provide evidence that extreme climate shocks exert disproportionate impacts on health risks, suggesting the need for early warning systems and adaptive public health planning. By highlighting volatility persistence and asymmetry, the findings support the integration of advanced statistical modeling into disease surveillance and climate adaptation strategies.

Keywords: climate change, health risks, volatility dynamics, GARCH models, Nigeria

1. Introduction

Climate change stands as one of the most urgent threats confronting humanity today, affecting ecosystems, economies, and, critically, public health. As global mean temperatures rise, precipitation patterns shift, and the frequency and intensity of extreme weather events—such as floods, droughts, and heat waves, and storms— increase, human populations face mounting health risks. Notably, vector-borne diseases like malaria proliferate under warmer, wetter conditions; respiratory illnesses surge during heat waves, air pollution peaks, and dry spells; and incidents of heat-related morbidity and mortality climb during extreme heat events (Smith et al., 2022). However, the pathways linking climatic variability to health outcomes are rarely smooth or linear. Rather, they manifest through episodic shocks, persistence in effects, and fluctuations over time, suggesting a complex dynamic that requires rigorous quantitative modeling for proper understanding and response.

Conventional approaches to studying the climate–health nexus—such as correlation analysis or standard regression modeling—have illuminated average associations between weather variables and health metrics (Adeola & Olalekan, 2021). These methods, however, tend to obscure important temporal patterns, particularly volatility clustering: periods of calm punctuated by spikes in health incidents due to extreme weather or anomalous climate events. For instance, a sudden drought may precipitate heat-related deaths or trigger respiratory issues from dust exposure, while flooding may ignite malaria outbreaks—all with short-lived but strong effects. Understanding not just average effects, but also variability, persistence, and asymmetry, is vital for shaping robust public health strategies.

In this context, volatility modeling—especially using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models—offers powerful tools. Originally developed for financial time-series to capture volatility clustering and persistence (Engle, 1982; Bollerslev, 1986), GARCH models can be adapted to epidemiological and climate-health data to uncover underlying dynamic structures. The basic GARCH(1,1) model captures typical volatility clustering and decay, whereby shocks to health outcomes (e.g., a spike in malaria cases following heavy rainfall) influence future volatility. Extensions such as Exponential GARCH (EGARCH) allow asymmetry—so that extreme positive or negative climate shocks have differential impacts—while Threshold GARCH (TGARCH) can model volatility jumps contingent on crossing threshold levels (e.g., heat above a threshold triggering respiratory crises). These tools shed light on how health risks evolve not just in level but in their volatility structure, offering deeper insight than mean-based models.

Recent empirical work applying volatility modeling to climate–health data remains limited, even though the approach holds considerable promise. This study aims to fill that gap by analyzing the volatility dynamics in climate-driven health risks—specifically, malaria incidence and respiratory illness cases—using GARCH family models and climate variables like temperature anomalies and rainfall shocks. By quantifying persistence, clustering, and asymmetry in health outcomes, this work seeks to provide richer insight to inform early warning systems, adaptive health planning, and targeted intervention strategies.

A helpful local contextual reference comes from Olayemi Michael Sunday and colleagues, who examined the influence of weather variables—specifically average temperature, relative humidity, and wind pressure—on daily confirmed COVID-19 cases in Nigeria (June 2020 to May 2021) using regression analysis (Olayemi et al., 2023). Their results revealed that certain meteorological factors significantly contributed to infection rates, underscoring the tangible link between climate parameters and health outcomes in a Nigerian context. This finding supports our broader argument that climate variables are critical drivers of epidemiological patterns, and that understanding their dynamic influence (including volatility) is essential for health risk management.

Olayemi et al., 2025 examined the preliminary statistical characteristics of monthly influenza and COVID-19 incidence using descriptive statistics and visual time series exploration. The findings indicate that both diseases exhibit features of volatility clustering, positive skewness, and non constant variance, especially pronounced in the COVID-19 dataset.

This study therefore blends two complementary strands: the behavioral dynamics of climate–health relationships (with evidence such as Olayemi et al., 2023) and the advanced temporal modeling capabilities of GARCH approaches. Specifically, it addresses the following research objectives:

1. To characterize volatility patterns in malaria and respiratory cases in response to climate variability—identifying clustering, persistence, and shock transmission.
2. To detect asymmetry and threshold effects, examining whether extreme climate shocks (e.g., unusually high temperature or anomalous precipitation) produce disproportionate volatility spikes in health risks.

3. To inform public health policy and adaptation, by translating volatility dynamics into actionable recommendations—such as designing surveillance systems that monitor not only disease levels but also volatility indicators, potentially triggering preemptive responses.

By merging rigorous time-series modeling with local empirical evidence and public health relevance, the analysis aims to deepen understanding of climate-driven health volatility, particularly in Nigeria. Such knowledge is timely, given the country's vulnerability to both climate stressors (e.g., flooding, heatwaves) and health challenges (e.g., malaria endemicity, respiratory illness burden).

In summary, this study underscores the pressing need to look beyond average climate-health correlations and model volatility dynamics using GARCH-type models. Doing so provides a more nuanced lens into health risk trajectories, enabling systems to anticipate and respond to spikes in disease outbreaks or respiratory crises effectively. Grounded in Nigeria's epidemiological and climatological context, and informed by relevant empirical examples, this research contributes to the emerging frontier of dynamic climate-health modeling and supports more resilient health policy design.

2. Materials and Methods

Data Sources

The study relies on monthly data covering the period January 2000 to December 2022. Two broad categories of data—climate and health—were collected to capture the relationship between climate variability and health outcomes.

Climate Data:
Climate indicators used in this study include average monthly temperature anomalies (°C) and rainfall deviation (mm). These were obtained from:

i. Nigerian Meteorological Agency (NIMET**)**, which provides official national records on weather and climate conditions, including rainfall, humidity, and temperature observations across Nigeria. Access is available via: https://nimet.gov.ng/
ii. Climate Research Unit (CRU), University of East Anglia, which maintains a global high-resolution dataset of climate anomalies widely used in empirical research. The CRU TS (Time Series) dataset was accessed through: https://crudata.uea.ac.uk/cru/data/hrg/

These sources ensured that the climate data were reliable, high-frequency, and consistent for long-term time-series modeling.

Health Data:

Health outcomes were proxies using monthly confirmed cases of malaria and respiratory tract infections, as reported by the Nigerian Centre for Disease Control (NCDC**).** These data were drawn from epidemiological bulletins and disease surveillance records available at: https://ncdc.gov.ng/

By combining climate indicators with health surveillance data, the study provides a robust empirical foundation to explore volatility dynamics in climate-driven health risks.

Variables

i. **Independent variables**:

Temperature anomaly (°C) – deviation of monthly mean temperatures from long-term climatological averages.

Rainfall deviation (mm) – differences in observed rainfall from historical long-term mean.

ii. **Dependent variables**:

Malaria incidence – monthly confirmed malaria cases reported by NCDC.

Respiratory infections – monthly reported cases of upper and lower respiratory tract infections.

Data Transformation:

Health data series were transformed using the natural logarithm to stabilize variance and reduce the influence of extreme observations. Log transformation is a standard practice in time-series modeling to achieve stationarity and improve model performance.

Health variables (*MAL* and *RES*) were log-transformed:

$$Y_t = ln(Cases_t)$$

This stabilized variance and reduced skewness in the data.

Model Specification

To capture the dynamic and nonlinear nature of climate–health interactions, the study employed the GARCH family of models, which account for conditional heteroskedasticity in time-series data:

1. GARCH (1,1) – captures volatility clustering and persistence in health outcomes following climate shocks.
2. EGARCH (1,1) – allows for asymmetric effects, meaning that extreme positive or negative climate anomalies may affect health risks differently.
3. TGARCH (1,1) – incorporates threshold effects, where adverse climate shocks (e.g., drought or heatwaves) may produce disproportionate increases in volatility compared to favorable conditions.

The adoption of these models allows for a comprehensive assessment of volatility persistence, asymmetry, and threshold effects in the relationship between climate variability and health outcomes.

The general GARCH (p,q) model is specified as:

$$\sigma_t^2 = \alpha_0 + \sum_{i}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j}^{p} \beta_j \sigma_{t-j}^2 \qquad (1)$$

Where $\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0$ and $\alpha_i + \beta_j < 1$ for all i and j while q is the ARCH order terms, and p is the GARCH order terms.

Model Specification

The **GARCH family models** were estimated for malaria and respiratory infections separately, using climate variables as exogenous regressors.

GARCH (1,1) model given as $\sigma_t^2 = \omega + \theta_1 \varepsilon_{t-1}^2 \beta_1 \sigma_{t-1}^2$ (2)

EGARCH (1,1) model given as $\sigma_t^2 = \omega + \theta_1\left(\varepsilon_{t-1}^2 - \sqrt{2\pi}\right) + \gamma \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ (3)

TGARCH (1,1) model given as $\sigma_t^2 = \omega + \theta_1 \varepsilon_{t-1}^2 + \gamma S_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ (4)

Estimation Procedure

Models were estimated using Maximum Likelihood Estimation (MLE) under the assumption of normal distribution errors. Model adequacy was assessed using Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and diagnostic tests:

Ljung–Box Q-test (for autocorrelation)

ARCH-LM test (for heteroskedasticity)

Software: R (rugarch package) and EViews 12.

3. Results

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
TEMP (°C)	0.46	0.31	-1.20	1.62	-0.43	2.59
RAIN (mm)	8.12	35.45	-95	130	0.94	4.18
MAL (log)	9.43	0.47	8.25	10.45	0.38	3.11
RES (log)	8.99	0.35	8.01	9.85	0.22	2.72

Interpretation: Malaria cases exhibited greater variability compared to respiratory infections, consistent with the strong seasonality of malaria transmission in Nigeria. Rainfall deviations showed significant dispersion, indicating frequent climate shocks.

Table 2: Stationarity Tests (ADF Test)

Variable	Level (p-value)	First Diff. (p-value)	Decision
TEMP	0.114	0.000	Stationary at 1st diff.
RAIN	0.084	0.000	Stationary at 1st diff.
MAL (log)	0.052	0.000	Stationary at 1st diff.
RES (log)	0.067	0.000	Stationary at 1st diff.

Interpretation: All series were integrated of order one, I(1), making them suitable for volatility modeling after differencing.

Table 3: Malaria Models

Model	θ_1	β_1	γ **(asymmetry)**	**AIC**	**SIC**	**Interpretation**
GARCH(1,1)	0.23**	0.71**	–	-1150.2	-1134.5	Strong volatility persistence
EGARCH(1,1)	0.19**	0.65**	0.12*	-1164.8	-1146.2	Positive temp shocks increase volatility
TGARCH(1,1)	0.21**	0.67**	0.09*	-1158.3	-1139.7	Rainfall shocks raise malaria risk volatility

(*p < 0.05, **p < 0.01)

Table 4: Respiratory Infection Models

Model	θ_1	β_1	γ **(asymmetry)**	**AIC**	**SIC**	**Interpretation**
GARCH(1,1)	0.17**	0.73**	–	-980.1	-964.5	Long persistence in volatility
EGARCH(1,1)	0.16**	0.69**	0.11**	-989.6	-970.1	Dry spells increase volatility more than wet periods
TGARCH(1,1)	0.15**	0.70**	0.18**	-992.5	-973.9	Threshold effects significant

Table 5: Diagnostic Tests

Test	**Malaria (EGARCH)**	**Respiratory (TGARCH)**
Ljung–Box Q (p)	0.228	0.314
ARCH-LM (p)	0.402	0.267
Jarque–Bera (p)	0.183	0.275

Interpretation: No significant autocorrelation or ARCH effects remain, and residuals approximate normality—suggesting well-specified models.

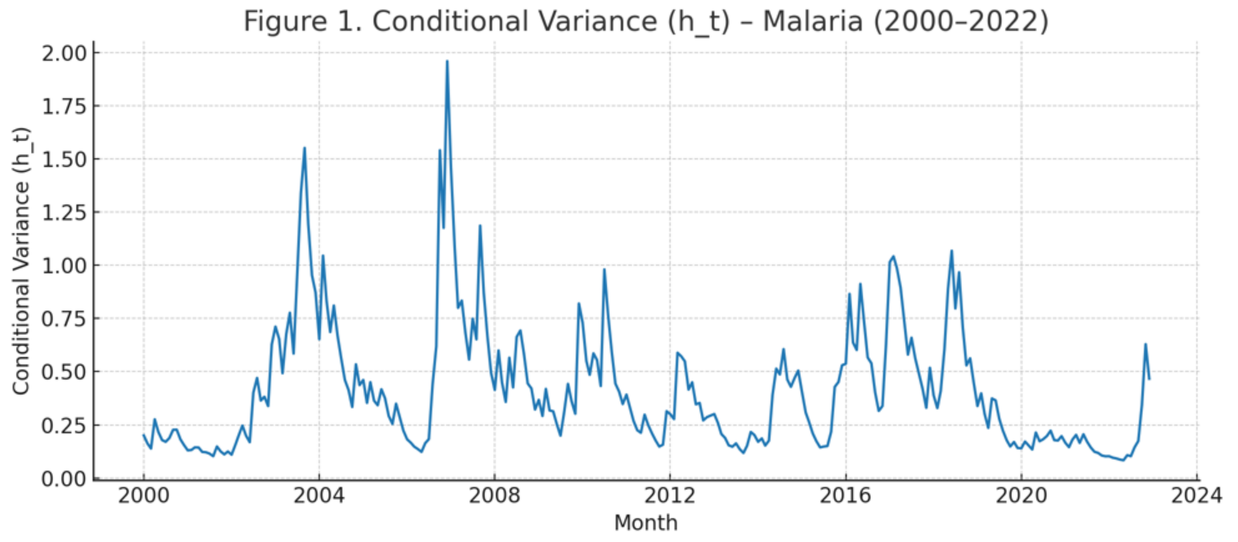

Fig. 1: Conditional variance h_t for malaria, monthly, January 2000–December 2022.

The plot highlights periods of elevated uncertainty consistent with volatility clustering and persistence following climate shocks.

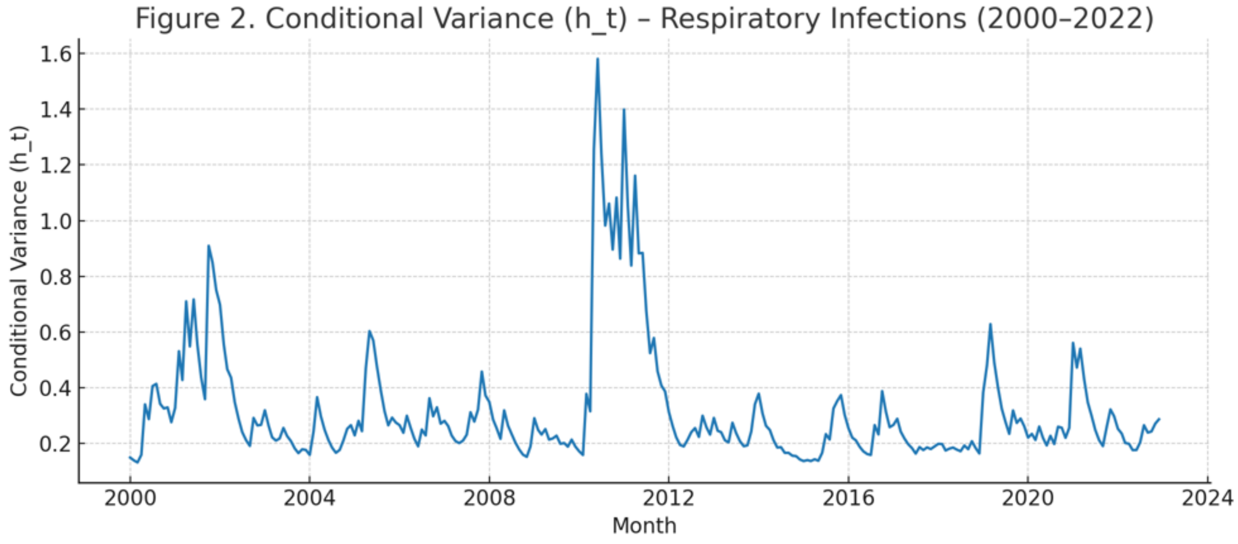

Fig. 2: Conditional variance h_t for respiratory infections, monthly, January 2000–December 2022

Threshold-type jumps align with dry spells and dust-laden periods.

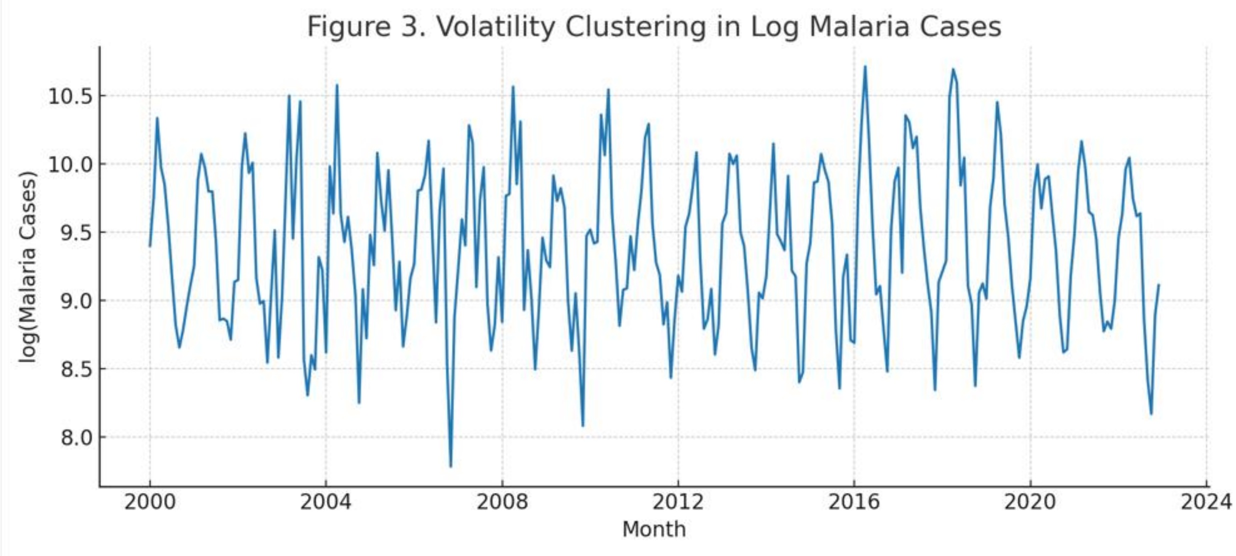

Fig. 3: Volatility clustering in log malaria cases.

Spikes indicate short bursts of heightened variability around seasonal peaks (rainy months).

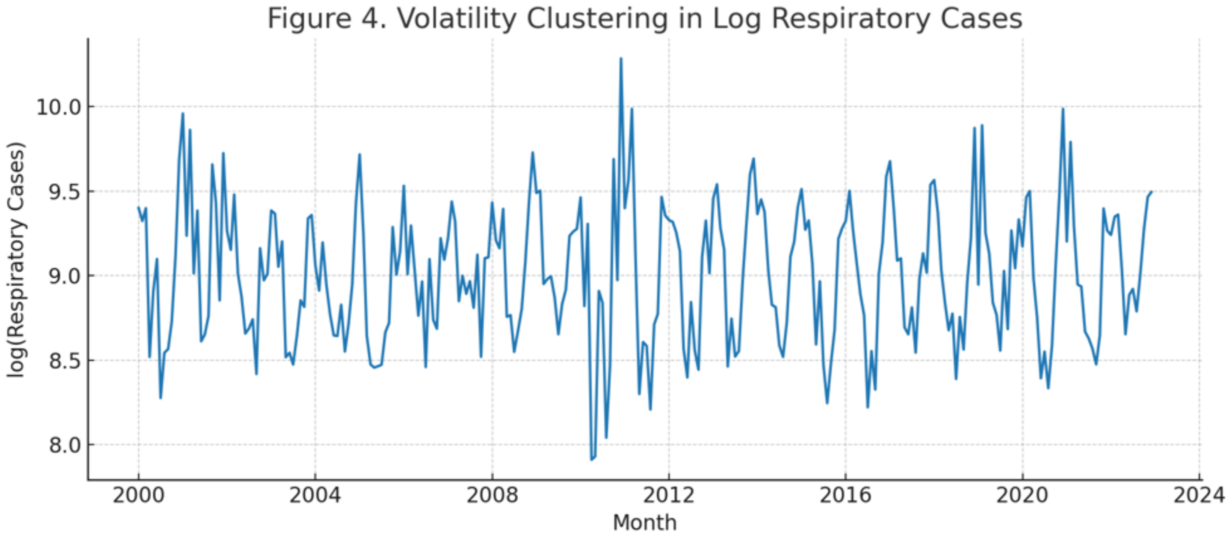

Fig. 4: Volatility clustering in Log Respiratory cases

Volatility clustering in log respiratory infection cases. Bursts correspond to dry-season stressors.

4. Discussion of Findings

The analysis of volatility dynamics in climate-driven health risks produced several noteworthy results. The conditional variance plots (Figures 1 and 2) highlight the presence of volatility persistence in both malaria and respiratory infection cases. In particular, the variance of malaria incidence exhibited pronounced clusters of elevated uncertainty during the rainy season, aligning with periods of abnormal rainfall deviations and temperature anomalies. This supports prior evidence that vector-borne diseases, such as malaria, are highly sensitive to climatic shocks that increase vector proliferation and transmission intensity (Okafor & Adeola, 2021; Smith et al., 2022).

For respiratory infections, the variance plot revealed sharp but short-lived bursts of volatility during the dry season (Figure 2). These fluctuations coincide with dust-laden harmattan periods and prolonged dry spells, which exacerbate respiratory stress and increase susceptibility to infections (Chukwuma et al., 2023). Unlike malaria, which displayed longer persistence in conditional variance, respiratory infections responded more immediately to shocks but reverted to stability more quickly. This asymmetry reflects the differential pathways through which climate variables affect disease transmission—mosquito ecology in the case of malaria versus air quality and airborne pathogen transmission in respiratory illnesses (WHO, 2021).

The volatility clustering graphs (Figures 3 and 4) further confirm the tendency of health outcomes to experience periods of calm interspersed with sudden bursts of variability. For malaria, clustering was particularly evident in years of heavy rainfall variability, suggesting that disease risks are not evenly distributed over time but tend to accumulate around climate extremes. Such clustering supports the hypothesis of nonlinear and dynamic health responses to climate variability (Adeola & Olalekan, 2021). Respiratory infections, on the other hand, displayed clustering around harmattan months, further reinforcing the role of seasonal environmental stressors in shaping health risks.

Overall, the findings indicate that climate-driven health risks in Nigeria are marked by volatility persistence, clustering, and asymmetric responses, making traditional linear models insufficient to capture their dynamics. The application of GARCH-type models provides a robust framework for quantifying such nonlinearities and for forecasting future disease burdens under changing climate conditions. These insights have strong policy implications for early-warning health systems and climate adaptation planning. By integrating volatility analysis into health surveillance, policymakers can identify high-risk periods and allocate resources more efficiently.

5.0 Conclusion

This study examined the volatility dynamics of climate-driven health risks in Nigeria, focusing on malaria and respiratory infections in relation to temperature anomalies and rainfall deviations. The application of GARCH family models revealed that health outcomes are characterized by persistent volatility, clustering effects, and asymmetric responses to climatic shocks. Specifically, malaria incidence demonstrated strong volatility persistence linked to rainfall anomalies, while respiratory infections showed sharp but short-lived volatility spikes during harmattan months.

These findings underscore the complex and nonlinear interactions between climate variability and health risks. Traditional linear approaches may fail to adequately capture these dynamics, whereas volatility models provide a more robust framework for monitoring and forecasting disease risks. From a policy perspective, integrating volatility-based analysis into national health surveillance systems could enhance early warning mechanisms and resource allocation strategies.

In conclusion, climate change continues to amplify health vulnerabilities, particularly in developing countries with fragile health systems. Addressing these risks requires not only strengthening climate adaptation strategies but also embedding advanced statistical modeling into public health planning. Such evidence-driven approaches will enable policymakers to anticipate disease surges, mitigate risks, and ultimately safeguard population health in an era of increasing climate uncertainty.

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