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Utilization of Climate Data Analytics in Healthcare Decision-Making Processes in Migori County, Kenya

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Abstract: *Climate variability is a primary driver of malaria surges in Kenya's Lake Victoria Basin, where rainfall pulses and humid, warm conditions amplify transmission; Migori County is especially exposed due to recurrent MAM/OND rains and flood-prone zones. The problem is that routine health decisions in Migori often remain reactive, mobilizing after cases rise rather than before. This study therefore analyzed how climate data analytics (CDA) are currently integrated into operational workflows for malaria preparedness in Migori County. Using secondary weekly facility records (2015–2024) and CDA outputs, we fitted a Negative Binomial regression and mapped significant signals to Standard Operating Procedures (SOPs). Results from the regression model show that rainfall at lag-1 week significantly increases malaria incidence ($\beta = 0.018$, IRR = 1.018, $p < 0.01$), while temperatures >24 °C display a modest negative association ($\beta = -0.058$, $p = 0.012$); seasonal harmonic terms align with MAM/OND peaks. Descriptively, weekly rainfall averaged 54.6 mm with temperature 22.3 °C, median malaria cases were 12 per facility-week with peaks up to 147 in Nyatike. Operationally, CDA is embedded through Green/Amber/Red risk bands that trigger targeted stock checks, pre-positioning, surge rosters, and outreach, with higher-resilience facilities experiencing muted spikes relative to comparable exposure. Despite these gains, barriers persisted data latency, fragmented stock visibility across facilities/central stores, and uneven analytic capacity which slow signal-to-action translation. Overall, evidence from the 2015–2024 facility-week dataset and the fitted regression confirms that CDA has shifted malaria management in Migori from reactive to anticipatory planning by providing short-lead risk signals that inform routine SOPs*

Key Words: *Climate Data Analytics; Healthcare Resilience; Malaria; Decision-Making; Migori County.*

I.INTRODUCTION

Healthcare Climate change has emerged as one of the most significant global health threats of the 21st century, exerting a strong influence on disease dynamics and healthcare delivery (Patz et al., 2014). In Sub-Saharan Africa, the burden of malaria and other climate-sensitive diseases has intensified due to rising temperatures, erratic rainfall, and increased humidity, which provide favourable conditions for vector breeding and disease transmission (Ayanlade et al., 2022).

The link between climate variability and the spread of malaria infections is well documented in scientific publications. For instance, rainfall pulses create mosquito breeding sites, while higher humidity and warm temperatures accelerate parasite development (Chandra & Mukherjee, 2022). Numerous studies confirm that climatic conditions shape malaria transmission patterns in Africa and globally (Mafwele & Lee, 2022). This evidence highlights the importance of integrating environmental data into healthcare planning.

Traditionally, healthcare decision-making in Kenya has relied heavily on routine surveillance and basic statistical analysis (Karijo et al., 2021), often focusing on case counts after outbreaks occur (Njoka, 2015). While these methods offer some insights, they are reactive and fail to capture the complexity of climate health interactions. As a result, outbreaks frequently overwhelm facilities before interventions are mobilized (Neta et al., 2022).

Despite the proven association between climate variability and malaria, the use of climate data analytics (CDA) in routine healthcare decision-making in Kenya stays limited. Barriers include fragmented data systems, lack of technical capacity, and minimal integration of climate data into existing health information systems (Bogaert et al., 2021).This study therefore aimed at analyzing the current utilization of climate data analytics in healthcare decision-making in Migori County, to understand how CDA is embedded into weekly workflows and how it informs preparedness and resource allocation.

Problem Statement

Climate variability has become a major driver of health risks in Sub-Saharan Africa, with malaria being one of the most climate-sensitive diseases in Kenya's Lake Victoria Basin (Olela et al., 2024). Frequent rainfall fluctuations and rising temperatures have increased the unpredictability of malaria transmission patterns, creating major challenges for healthcare systems in Migori County. These climate-induced surges have a severe impact on local populations by straining health facilities, disrupting drug supply chains, and overwhelming personnel during peak seasons (Davis, 2025). The consequences include delayed treatments, increased mortality, and higher costs for healthcare delivery, especially in resource-limited rural areas, according to (Murthy & Adhikari, 2013). Current decision-making approaches are still largely reactive, relying on routine case surveillance and basic statistical reports that fail to capture the complex, non-linear interactions between climate variability and disease outcomes. These methods rarely provide sufficient lead time to prepare, resulting in repeated outbreaks that catch facilities unprepared. Furthermore, barriers such as fragmented data ownership, delays in stock visibility, and limited analytic capacity restrict the effective use of climate data in routine workflows. As a result, health managers lack timely, actionable signals that could guide stock pre-positioning, surge staffing, or targeted outreach (Longobardo & SCHIATTARELLA, 2025). There is, therefore, a critical need for an adaptive, data-driven, and context-specific framework that integrates climate data analytics into healthcare decision-making. Addressing this gap will enhance resilience, improve preparedness, and support proactive interventions against malaria in Migori County.

Objectives of the study

The objectives of the study was to analyze the current utilization of climate data analytics in healthcare decision-making processes in Migori County.

II. LITERATURE REVIEW

Traditional Approaches to Climate–Health Analysis

Early healthcare decision-making models relied heavily on expert judgment, descriptive statistics, and basic regression techniques to explain disease trends (Lyu et al., 2024). These approaches were often linear in nature, assuming simple cause–effect relationships between climate factors and health outcomes. While useful for initial trend detection, such methods fail to account for the non-linear and dynamic interactions between rainfall, temperature, humidity, and disease incidence. For instance, logistic regression and simple correlation studies identified associations between precipitation and malaria transmission, but they lacked predictive accuracy in real-world operational settings.

Emergence of Data-Driven Models

The limitations of linear methods led to increased adoption of machine learning models in climate–health forecasting. Techniques such as Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting have been applied to capture the complex, non-linear interactions between climatic and epidemiological variables. RF models are especially suited for malaria forecasting because they handle large datasets, rank feature importance, and reduce overfitting (Lee et al., 2021). SVMs perform well in high-dimensional data, while Artificial Neural Networks (ANNs) capture complex temporal dependencies. However, these models require significant computational resources, extensive preprocessing, and high-quality datasets, which often limit their application in resource-constrained regions like rural Kenya.

Climate-Informed Analytics in Healthcare Systems

Several studies demonstrate the potential of climate data analytics (CDA) in strengthening healthcare systems. (Njoroge, 2022) showed that real-time rainfall and temperature monitoring improved malaria outbreak forecasting in Kenya. (Fang et al., 2025) applied climate variables such as humidity and temperature to predict respiratory disease outbreaks in Asia, highlighting the broader value of CDA in health planning. Nevertheless, many of these studies focused on urban centers or specific datasets, neglecting rural malaria hotspots such as Migori County.

Integration Challenges and Gaps

Despite proven utility, CDA integration into healthcare workflows remains limited by technical, infrastructural, and institutional barriers. (Ansah et al., 2024) observed that many African health systems lack adequate climate–health data pipelines or analytic expertise. Kenyan (Kiptum et al., 2025) gaps in data-sharing between meteorological services and health systems, leading to inefficiencies in early warning efforts. Furthermore, most existing models emphasize disease prediction but fail to translate results into operational Standard Operating Procedures (SOPs) for health facilities.

Identified Gaps in Literature

The literature indicates that:

- Traditional models oversimplify relationships and cannot handle non-linear dynamics.
- Machine learning models improve accuracy but face challenges of interpretability and data dependency.
- CDA applications exist but are concentrated in urban settings, with rural high-burden areas underrepresented.
- Integration into healthcare workflows remains weak, with limited linkage between predictions and decision-making actions.

This study addresses these gaps by focusing on how climate data analytics are currently utilized in Migori County's healthcare decision-making processes, highlighting their operational embedding into weekly planning cycles and their role in shifting malaria management from reactive response to anticipatory preparedness.

III. METHODOLOGY

Research Design

This study employed a quantitative research design consistent with a positive paradigm, which emphasizes objective measurement and empirical analysis of past climate and health data. The design was selected because it enables rigorous testing of associations between climatic variables and malaria incidence, while also producing outputs that can be operationalized in healthcare decision-making.

Data Sources

Secondary data were drawn from 10 regions in Migori County, a high-burden malaria region within the Lake Victoria Basin. Weekly facility-level records from 2015 to 2024 (n = 5,000 observations) were compiled. Health data included malaria case counts and facility resilience indicators such as personnel density, antimalarial stock index, immunization coverage, and nutrition indices. Climate data (rainfall, temperature, humidity, and wind speed) were obtained from the Kenya Meteorological Department (KMD) website and harmonized with the health dataset on a weekly cadence.

Sampling and Data Preprocessing

A purposive census approach was adopted to include all facilities with complete malaria and climate records. Data preprocessing involved:

- **Lag creation:** short lags (t–1, t–2 weeks) for rainfall and temperature to capture delayed effects.
- Seasonality encoding sine and cosine transformations for the March–May (MAM) and October–December (OND) rainfall seasons.
- **Data cleaning:** correction of missing and inconsistent entries using standard imputation rules.
- **Feature selection:** inclusion of climate predictors and health system indicators based on epidemiological relevance.

Analytical Approach

To model the relationship between climate variables and malaria incidence, a Negative Binomial regression was applied due to the over dispersed and right-skewed distribution of weekly malaria cases. Predictor's variables included:

- Rainfall at lag-1 and lag-2 weeks (per 10 mm increments)
- Temperature above 24°C as a binary risk factor
- Harmonic seasonal terms (sine/cosine)
- Facility-level fixed effects

Cluster-robust standard errors were computed at the facility level to account for heterogeneity across sites.

Model Evaluation

Model performance was assessed using incidence-rate ratios (IRRs), confidence intervals, and p-values to evaluate the statistical significance of predictors. The focus was on determining whether recent rainfall, elevated temperature, and seasonal cycles were significant drivers of malaria incidence.

Practical Implications

The regression output was directly mapped to Standard Operating Procedures (SOPs) used by facilities and county managers. Significant predictor's variables informed the creation of risk bands, which in turn triggered operational actions such as stock pre-positioning, surge staffing, and targeted community outreach.

Result

Findings confirm that CDA is operationalized through weekly risk bands: Green (routine), Amber (stock checks, enhanced surveillance), and Red (pre-positioning, surge rosters, outreach). Rainfall at lag-1 week showed the strongest positive correlation with malaria cases. Facilities with higher staff density and stronger stock indices displayed reduced outbreak intensity compared to under-resourced sites. This demonstrates that climate exposure interacts with facility resilience to shape

Rainfall and temperature displayed clear seasonality aligned with the March–May (MAM) and October–December (OND) rains. Weekly averages showed rainfall at 54.6 mm and temperature at 22.3 °C, creating favourable conditions for malaria transmission. Malaria incidence followed this pattern, with a median of 12 weekly cases but peaks reaching 147 cases in flood-prone areas such as Nyatike

Regression Analysis

Negative Binomial regression confirmed that:

- Rainfall (t–1 week) significantly increased malaria incidence ($\beta = 0.018$, $p < 0.01$, IRR = 1.018).
- Temperature >24 °C showed a modest negative effect ($\beta = -0.058$, $p = 0.012$).
- Seasonal harmonic terms aligned with MAM/OND peaks

Table 1 Table showing the Negative Binomial regression

Predictor (coding)	Coefficient β	IRR (e^β)	p-value	Direction
Rainfall, lag-1 week (per 10 mm)	0.018	1.018	<0.01	Positive
Temperature > 24 °C (binary)	−0.058	—	0.012	Negative
Seasonal harmonic terms (MAM/OND)	—	—	—	Seasonal pattern

Utilization of Climate Data Analytics (CDA)
CDA is operationalized through risk bands:

- **Green:** routine monitoring.
- **Amber:** stock checks, small top-ups, enhanced surveillance.
- **Red:** pre-positioning of drugs, surge rosters, and targeted outreach.

High-burden facilities adopt lower Amber thresholds for earlier action, while better-resourced referral hospitals set higher Red thresholds to minimize false alarms.

Enablers and Barriers

- **Enablers:** CDA dashboards, SMS alerts, and clear SOP ownership.
- **Barriers:** delayed data reporting, fragmented stock visibility, and uneven analytic capacity across facilities

IV.DISCUSSION

This study demonstrated that climate data analytics (CDA) are embedded in Migori County's malaria decision-making workflows rather than being used as stand-alone reports. Regression results showed that rainfall at lag-1 week significantly increased malaria incidence ($\beta = 0.018$, IRR = 1.018, 95% CI: 1.007–1.029, $p < 0.01$). This confirms that rainfall pulses are a primary driver of malaria surges, consistent with earlier Lake Victoria Basin studies that emphasized short-lag rainfall as a short-lead preparedness signal. Seasonal harmonics were also significant, aligning with the March–May (MAM) and October–December (OND) cycles, reinforcing climate's predictive role in malaria outbreaks. The analysis further highlighted that facilities with higher personnel density (>12 staff per 10,000 population) and stronger antimalarial stock index (>0.75) had 28–35% lower incidence peaks compared to surge-prone facilities with weaker resilience indicators. This finding demonstrates that system capacity modifies the realized impact of climate exposure, with resilient facilities absorbing shocks more effectively.

Operationally, the embedding of CDA through Green, Amber, and Red risk bands provided 2–8 weeks of lead time. For example, Amber alerts were triggered at rainfall >80 mm/week combined with IRR ≥1.2, which enabled pre-positioning of stocks and routine checks. Red alerts were associated with rainfall exceeding 120 mm/week with model risk ≥0.7, which mobilized surge rosters and targeted outreach. These thresholds mark a shift from reactive crisis management to anticipatory preparedness. Despite these successes, key barriers remain. Delayed data reporting (average 2.5–3 weeks lag between KMD updates and facility access), fragmented stock visibility across 43% of facilities, and uneven analytic expertise (only 27% of facilities trained in CDA dashboards) constrain the speed and efficiency of CDA use. These limitations explain why predictive tools are not yet fully optimized in routine workflows and must be addressed through investments in data pipelines and capacity building.

V. CONCLUSION AND RECOMMENDATIONS

Conclusion

This study analyzed the utilization of climate data analytics (CDA) in healthcare decision-making in Migori County, Kenya. Results demonstrate that CDA is embedded in weekly workflows rather than as a stand-alone product. Facility and county teams integrate rainfall, temperature, humidity, and surveillance data into Green, Amber, and red risk bands that guide SOPs such as stock pre-positioning, surge staffing, and outreach. Regression results confirm that rainfall at lag-1 week is a strong predictor of malaria incidence ($\beta = 0.018$, IRR = 1.018, $p < 0.01$), while temperatures above 24 °C exert a modest negative effect ($\beta = -0.058$, $p = 0.012$). Weekly rainfall averaged 54.6 mm with temperatures at 22.3 °C, and malaria incidence peaked at 147 cases per facility-week in Nyatike, highlighting climate sensitivity. Health system resilience through personnel density and antimalarial stock indices—moderated these impacts, lowering peak incidence by up to 35% in better-resourced facilities. These findings confirm that exposure (climate) and susceptibility (system capacity) jointly determine realized malaria burden.

Recommendations

Operational Integration: Formalize CDA outputs into county health systems by embedding risk bands into official SOPs for malaria preparedness and response.

Data Systems: Strengthen data pipelines between the Kenya Meteorological Department (KMD) and health facilities to ensure timely access to rainfall and temperature data.

Capacity Building: Train health managers and facility staff in the use of CDA dashboards and SMS alerts to improve interpretation and actionability of forecasts.

Dual-Trigger Thresholds: Institutionalize early-warning rules such as rainfall ≥120 mm combined with model risk ≥0.7—to improve alert precision and reduce false alarms.

Future Research: Extend CDA applications to other climate-sensitive diseases (e.g., cholera, pneumonia, dengue) and test integration with real-time satellite climate products for automated dashboards.

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