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Spatio-Temporal Random Effects Modeling of Malaria Incidence and Mortality in Kenya

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Abstract: Malaria is a major public health challenge in sub-Saharan Africa, with transmission patterns that vary significantly across space and time due to environmental, socioeconomic, and epidemiological factors. These variations complicate efforts to design effective and targeted interventions, making it crucial to understand the dynamics of disease spread. This study employed Bayesian spatio-temporal random effects modeling framework to analyze malaria incidence and mortality ratio across Kenya. The approach incorporated spatial and temporal dependencies to provide a detailed understanding of malaria incidence and mortality risk patterns. Spatial random effects were modeled using conditional autoregressive (CAR) priors to account for correlations among neighboring counties, while temporal dependence was captured using autoregressive processes of order two (AR2), reflecting trends over multiple time periods. An evaluation was on the performance of Spatio-Temporal Poisson Linear Trend Model (STPLM), Spatio-Temporal Poisson ANOVA Model (STPAM), Spatio-Temporal Poisson Separable Model (STPSM) and Poisson Temporal Model for Spatio-Temporal Effects (PTSTN)using the Deviance Information Criterion (DIC), the effective number of parameters ($p.d$) and the Log Marginal Pseudo-Likelihood (LMPL). The Spatio-Temporal Poisson ANOVA Model (STPAM) was found as the best Poissson Spatial-Temporal Model and was used to develop a multivariate spatio-temporal model for the joint modeling of malaria incidence and mortality. Using the developed model, the study identified significant spatial clustering of malaria, with persistent high-risk zones in western and coastal counties. Temporal trends indicated an overall decline in transmission, though progress was uneven across counties, reflecting differences in intervention coverage, healthcare access, and local epidemiology. These findings underscored the value of multivariate spatio-temporal modeling of malaria incidence and mortality for guiding malaria control strategies. This study thus demonstrates that Bayesian Spatial-Temporal modeling is essential for understanding heterogeneous malaria incidence and mortality risk and informing strategies aimed at reducing disease burden and advancing toward malaria elimination in Kenya.

Keywords: Spatio-temporal Modeling, Malaria Incidence, Bayesian Hierarchical Models, Spatial Random Effects

1. Introduction

Malaria remains one of the most serious public health concerns in sub-Saharan Africa, continuing to cause high levels of illness and death despite extensive control measures [30]. According to the World Health Organization (WHO, 2024), Africa accounts for about 94% of global malaria cases and fatalities, with children under five and pregnant women being the most vulnerable [2, 16]. In Kenya, this disparity is even more evident, with lake-endemic and western counties such as Busia, Kakamega, Kisumu, Migori, Siaya, and Vihiga recording incidence rates as high as 748 cases per 1,000 population, compared to the national average of around 104 per 1,000 [22, 25]. Although interventions such as insecticide-treated nets, indoor residual spraying and effective

diagnosis and treatment have reduced malaria prevalence over the past two decades, these achievements have been uneven across regions [5, 26]. The intensity of malaria transmission varies considerably across space and time, making it essential to understand these patterns for more targeted and effective control strategies [6, 7].

Spatio-temporal statistical modeling provides a robust framework for analyzing diseases that vary geographically and temporally [21, 22]. Unlike traditional regression models, spatio-temporal random effects models explicitly account for spatial dependence and temporal correlation, leading to more accurate and reliable inferences [9, 13]. These models have been widely applied in epidemiology to map disease risks, monitor transmission dynamics and improve outbreak predictions [11, 29]. Advances in Bayesian hierarchical modeling and the use of integrated nested Laplace approximation (INLA) have made it feasible to conduct detailed, large-scale spatio-temporal analyses with improved computational efficiency [15, 18].

In malaria research, spatio-temporal modeling plays a crucial role in revealing variations in disease risk and identifying areas with persistent or emerging transmission [14, 20]. Previous studies have demonstrated its ability to detect spatial clusters and monitor changes in malaria trends across multiple geographic scales as with [10, 22, 25, 27, 30]. This study, therefore, sought to evaluate spatio-temporal random effects models with the objective of identifying the most suitable model for accurately capturing and explaining the spatial and temporal variations in malaria incidence and mortality across Kenya in a multivariate framework.

1.1. Statement of Problem

Reported malaria cases and deaths have remained high in Kenya and progress toward elimination has been uneven across regions. Despite extensive control measures, malaria continues to impose a major health burden in Kenya, with persistent transmission in some counties while others experience notable declines. This uneven progress reflects the influence of complex spatial and temporal dynamics that are not yet fully understood. Understanding how malaria incidence and mortality vary across space and time is therefore crucial for informing more effective and geographically targeted interventions.

Most existing studies in Kenya have relied on univariate or cross-sectional analyses that treat incidence and mortality separately, overlooking how these outcomes evolve together across regions and over time[6, 10, 15, 23]. This limitation has hindered the identification of persistent hotspots and emerging transmission zones, reducing the effectiveness of malaria control efforts. To address this gap, a multivariate spatio-temporal modeling framework is required to jointly analyze malaria incidence and mortality while accounting for their spatial and temporal dependencies. Such an approach can uncover co-occurring risks and evolving disease patterns, providing essential insights for data-driven strategies to reduce malaria transmission and mortality across Kenya.

1.2. Research Objectives

The study objectives were;

1.2.1. General Objective

The general objective of this study was to determine the most appropriate spatio-temporal random effects model to use in the modeling of malaria incidence and mortality in a multivariate framework.

1.2.2. Specific Objectives

The specific objectives were;

1. Model malaria incidence and Mortality using Poisson Spatio-temporal Random Effects Models.
2. Estimate model parameters for the proposed Poisson Spatio-temporal Random Effects Models in the modeling of malaria incidence and Mortality.
3. Determine the best Poisson Spatio-temporal Random Effects Model to use in the modeling of malaria incidence and Mortality in a multivariate framework.
4. Use the determined model to develop a Poisson Multivariate Spatio-temporal Random Effects Model for modeling of malaria incidence and Mortality

2. Literature Review

Spatial and spatio-temporal modeling techniques are key in epidemiological research, they help researchers capture spatial heterogeneity and temporal dynamics of disease prevalence as with the case of malaria across regions [4, 28]. In this regard, Aheto *et al.*[1] and Munyenyembe *et al.* [18] used Bayesian spatio-temporal frameworks to identify localized hotspots of high transmission in Ghana and Malawi, while Noor *et al.* [19] and Macharia *et al.* [17] combined health facility and survey data to uncover persistent malaria clusters in Namibia and Kenya despite overall declines in prevalence. Armando *et al.* [3] and Rutto *et al.* [25] demonstrated that rainfall, temperature and vegetation significantly influence malaria risk across Mozambique and Kenya. Similarly, Ouma *et al.* [23] and Paaijmans *et al.* [24] showed that temporal fluctuations in precipitation and humidity shape mosquito breeding cycles and subsequent disease incidence.

Otambo *et al.* [22] and Wanjala *et al.* [31, 32] further revealed that changes in mosquito abundance and species composition, coupled with climate variation, contribute to malaria resurgence in previously low-risk zones. Apeagyei *et al.* [2] and Lacey *et al.* [15] reported that inequities in health investment and service accessibility perpetuate transmission in marginalized areas, while Kamau *et al.* [10] highlighted how housing conditions, population density and facility access influence malaria incidence. Moreover, Gwitira *et al.* [8] and Katale and Gemechu [12] demonstrated that urbanization and land-use changes modify local vector habitats, altering human exposure patterns.

3. Methodology

This study evaluated the performance of Spatio-Temporal Poisson Linear Trend Model (STPLM), Spatio-Temporal Poisson ANOVA Model (STPAM), Spatio-Temporal Poisson Separable Model (STPSM) and Poisson Temporal Model for Spatio-Temporal Effects (PTSTN) in the modeling of malaria incidence and mortality in a multivariate framework.

3.1. Spatio-Temporal Random Effects Models

Spatio-temporal random effects models capture spatial dependence and temporal correlation simultaneously, enabling a comprehensive analysis of how malaria incidence and mortality varies across counties and over time in Kenya. Let Y_{it} denote the malaria incidence ratio in county i $(i = 1, 2, \ldots, 47)$ during year t $(t = 1, 2, \ldots, 10)$ assumed to follow a Poisson distribution.

The expected incidence mortality ratio of county i at time t is represented by η_{it}. The mean μ_{it} is specified as;

$$\log(\mu_{it}) = \eta_{it} + \psi_{it}. \tag{1}$$

The random effect ψ_{it} accounted for unobserved spatial and temporal heterogeneity in the reporting of malaria incidence ratio in Kenya and was decomposed to capture distinct spatio-temporal structures through Poisson CAR model formulations.

3.1.1. Spatio-Temporal Poisson Linear Trend Model (STPLM)

A widely used extension is the spatio-temporal Poisson linear trend model, which incorporates a county-specific linear temporal trend in the random effects for each area (i). The model is expressed as

$$\psi_{it} = \beta_1 + \phi_i + (\beta_2 + \delta_i)\frac{t - \bar{t}}{T}, \tag{2}$$

where T denotes the total number of time periods and β_1 and β_2 represent the overall intercept and temporal slope, respectively [12]. The terms ϕ_i and δ_i denote county-specific intercepts and slopes capturing spatially varying temporal trends. These parameters follow conditional autoregressive (CAR) priors with distinct spatial dependence and variance parameters as $\boldsymbol{\phi} \sim \text{NCAR}(\phi \mid \rho_{\text{int}}, \tau^2_{\text{int}}, W)$ and $\boldsymbol{\delta} \sim \text{NCAR}(\delta \mid \rho_{\text{slo}}, \tau^2_{\text{slo}}, W)$.

$$\phi_i \mid \phi_{-i}, W \sim N\left(\frac{\rho_{\text{int}} \sum_{j=1}^{i} w_{kj}\phi_j}{\rho_{\text{int}} \sum_{j=1}^{i} w_{kj} + 1 - \rho_{\text{int}}}, \frac{\tau^2_{\text{int}}}{\rho_{\text{int}} \sum_{j=1}^{i} w_{kj} + 1 - \rho_{\text{int}}}\right),$$
$$\delta_i \mid \delta_{-i}, W \sim N\left(\frac{\rho_{\text{slo}} \sum_{j=1}^{i} w_{kj}\delta_j}{\rho_{\text{slo}} \sum_{j=1}^{i} w_{kj} + 1 - \rho_{\text{slo}}}, \frac{\tau^2_{\text{slo}}}{\rho_{\text{slo}} \sum_{j=1}^{i} w_{kj} + 1 - \rho_{\text{slo}}}\right)$$

The spatial dependence parameters ρ_{int} and ρ_{slo} are assigned uniform priors on $(0, 1)$, while the variance components τ^2_{int} and τ^2_{slo} follow inverse-gamma priors to account for uncertainty in spatial variability.

3.1.2. Spatio-Temporal Poisson ANOVA Model (STPAM)

This model relaxes the linearity assumption in temporal trends. It captures additive spatial and temporal main effects without interactions, later extended to include space-time interaction terms through an ANOVA-type decomposition. The model is expressed as

$$\begin{aligned} \psi_{it} &= \phi_i + \delta_t + \gamma_{it}, \\ \gamma_{it} &\sim N(0, \tau_I^2) \end{aligned} \tag{3}$$

where ϕ_i denotes spatial effects, δ_t represents temporal effects and γ_{it} accounts for space-time interactions (Knorr-Held, 2000). Each component is modeled as a random effect with its own distribution as $\phi \mid \rho_S, \tau_S^2, W \sim \text{NCAR}(\phi \mid \rho_S, \tau_S^2, W)$ and $\delta \mid \rho_T, \tau_T^2, D \sim \text{NCAR}(\delta \mid \rho_T, \tau_T^2, D)$.

$$\phi_i \mid \phi_{-i}, W \sim N\left(\frac{\rho_S \sum_{j=1}^{i} w_{kj}\phi_j}{\rho_S \sum_{j=1}^{i} w_{kj} + 1 - \rho_S}, \frac{\tau_S^2}{\rho_S \sum_{j=1}^{i} w_{kj} + 1 - \rho_S}\right)$$
$$\delta_t \mid \delta_{-t}, D \sim N\left(\frac{\rho_T \sum_{j=1}^{N} d_{tj}\delta_j}{\rho_T \sum_{j=1}^{N} d_{tj} + 1 - \rho_T}, \frac{\tau_T^2}{\rho_T \sum_{j=1}^{N} d_{tj} + 1 - \rho_T}\right)$$

where W and D are spatial and temporal adjacency matrices, respectively, with $d_{ij} = 1$ if $|i - j| = 1$ and $d_{ij} = 0$ otherwise.

The dependence parameters ρ_S and ρ_T follow independent Uniform$(0, 1)$ priors, while the variance terms τ_S^2, τ_T^2 and τ_I^2 follow inverse-gamma priors.

3.1.3. Spatio-Temporal Poisson Separable Model (STPSM)

The Poisson Spatio-Temporal Separable Model incorporates both an overall temporal trend and temporally varying spatial effects. Here, the spatial effects for each time t are represented as $\boldsymbol{\phi}_t = (\phi_{1t}, \phi_{2t}, \ldots, \phi_{47t})^\top$ for $t = 1, \ldots, 10$, while the temporal effects are given by $\boldsymbol{\delta} = (\delta_1, \delta_2, \ldots, \delta_{10})^\top$ (Napier *et al.*, 2016). These components follow NCAR priors:

$$\begin{aligned} \psi_{it} &= \phi_{it} + \delta_t \\ \phi_{it} \mid \phi_{-i,t}, W &\sim N\left(\frac{\rho_S \sum_{j=1}^{i} w_{kj}\phi_{jt}}{\rho_S \sum_{j=1}^{i} w_{kj} + 1 - \rho_S}, \frac{\tau_S^2}{\rho_S \sum_{j=1}^{i} w_{kj} + 1 - \rho_S}\right) \\ \delta_t \mid \delta_{-t}, D &\sim N\left(\frac{\rho_T \sum_{j=1}^{N} d_{tj}\delta_j}{\rho_T \sum_{j=1}^{N} d_{tj} + 1 - \rho_T}, \frac{\tau_T^2}{\rho_T \sum_{j=1}^{N} d_{tj} + 1 - \rho_T}\right) \end{aligned} \tag{4}$$

where D retains the temporal adjacency structure defined previously. The spatial and temporal dependence parameters, ρ_S and ρ_T, are assigned independent Uniform$(0, 1)$ priors, while the variance components τ_t^2 and τ^2 follow inverse-gamma priors.

3.1.4. Poisson Temporal Model for Spatio-Temporal Effects (PTSTN)

A simplified version of the separable model assumed a first-order temporal autoregressive process, in which the temporal effect δ_t was set to zero for all t (Rushworth *et al.*, 2014). The model was therefore specified as;

$$\begin{aligned}
\psi_{kt} &= \phi_{kt} \\
\phi_t \mid \phi_{t-1} &\sim \mathcal{N}(\rho_{T1}\phi_{t-1}, \tau^2 Q(W,\rho_S)^{-1}), \\
& t = 2,\ldots,13 \quad \text{(AR1)} \\
\phi_t \mid \phi_{t-1},\phi_{t-2} &\sim \mathcal{N}\Big(\rho_{T1}\phi_{t-1} + \rho_{T2}\phi_{t-2},\ \tau^2 Q(W,\rho_S)^{-1}\Big), \\
& t = 3,\ldots,13 \quad \text{(AR2)} \\
\delta_t \mid W &\sim \mathcal{N}(0, \tau^2 Q(W,\rho_S)^{-1})
\end{aligned} \tag{5}$$

Beyond the first-order specification, a second-order temporal auto-regressive process allowed the model to capture more complex temporal dependencies. The random effects were assumed to be zero-mean centered, while flat and conjugate inverse-gamma priors were specified for $(\rho_S, \rho_T, \rho_{T1}, \rho_{T2})$ and τ^2 respectively, with $(a = 1, b = 0.01)$ taken as the default hyper-parameter values for the latter.

3.2. Poisson Multivariate Spatio-Temporal Areal Model

The Poisson multivariate spatio-temporal areal model allowed for the simultaneous modeling of malaria incidence and mortality across spatial units (Counties) and time periods. By incorporating spatial and temporal random effects, it effectively captured the shared spatial temporal dependencies and correlations which led to more accurate and insightful inference on malaria incidence and mortality dynamics.

Let Y_{ktj} be the observed malaria incidence and mortality for the k^{th} county ($k = 1,\ldots,47$) during the t^{th} time period ($t = 1,\ldots 13$) for the j^{th} response ($j_1 =$ Malaria Incidence and $j_2 =$ Malaria Mortality, with η_{ktj} as an offset. The Poisson multivariate spatio-temporal model was formulated as;

$$\begin{aligned}
Y_{ktj} \mid \mu_{ktj} &\sim \text{Poisson}(\mu_{ktj}), \\
\log(\mu_{ktj}) &= \boldsymbol{\beta}_0 + \eta_{ktj} + \psi_{ktj}, \\
\boldsymbol{\beta}_0 &\sim N(\boldsymbol{\mu}_\beta, \boldsymbol{\Sigma}_\beta),
\end{aligned} \tag{6}$$

where $\mu_{ktj} = \mathbb{E}(Y_{ktj})$ is the expected value of Y_{ktj}, $\boldsymbol{\beta}_0$ is the intercept and ψ_{ktj} are spatio-temporal random effects that accounted for correlations across space, time and malaria incidence and mortality.

The random effects $\{\psi_{ktj}\}$ were modeled using a single set of latent effects $\{\phi_{ktj}\}$ that were correlated across all dimensions as;

$$\begin{aligned}
\psi_{ktj} &= \phi_{ktj}, \\
\boldsymbol{\phi} &\sim N\big(\mathbf{0}, \mathbf{D}(\alpha) \otimes \mathbf{Q}(W,\rho_S) \otimes \boldsymbol{\Sigma}^{-1}\big),
\end{aligned} \tag{7}$$

where $\mathbf{D}(\alpha)_{N\times N}$ captured temporal autocorrelation, $\mathbf{Q}(W,\rho_S)_{K\times K}$ encoded spatial dependencies using a CAR prior and $\boldsymbol{\Sigma}_{J\times J}$ modeled the covariance between malaria incidence and mortality.

Spatial correlations wre specified via the Leroux CAR prior as;

$$\begin{aligned}
\mathbf{Q}(W,\rho_S) &= \rho_S(\text{diag}[W\mathbf{1}] - W) + (1-\rho_S)\mathbf{I}, \\
\rho_S &\sim \text{Uniform}(0,1),
\end{aligned} \tag{8}$$

where ρ_S determined the strength of spatial dependence.

Temporal correlations were incorporated through autoregressive processes of order two as;

$$\phi_t \mid \phi_{t-1},\phi_{t-2} \sim N\big(\rho_{T1}\phi_{t-1} + \rho_{T2}\phi_{t-2}, \mathbf{Q}(W,\rho_S) \otimes \boldsymbol{\Sigma}^{-1}\big), \phi_1, \phi_2 \sim N\big(0, \mathbf{Q}(W,\rho_S) \otimes \boldsymbol{\Sigma}^{-1}\big). \tag{9}$$

The outcome covariance matrix $\boldsymbol{\Sigma}$ was assigned a weakly informative scale-mixture Inverse-Wishart prior, allowing the correlations between malaria incidence and mortality to be inferred from the data without imposing strong prior assumptions.

In this model, the variance parameter τ^2 captured unexplained variability in malaria incidence and mortality, while the spatial autocorrelation parameter ρ_S measured similarity across neighboring counties and the temporal autocorrelation parameter ρ_T described malaria incidence/mortality persistence over time.

3.3. Parameter Estimation

Parameter estimation was performed using Markov Chain Monte Carlo (MCMC) to explore the joint posterior of the latent spatio-temporal field $\mathbf{x} = (u_i, v_t, w_{i,t})$ and hyperparameters $\boldsymbol{\theta}$:

$$\pi(\mathbf{x}, \boldsymbol{\theta} \mid \mathbf{y}) \propto \pi(\boldsymbol{\theta})\,\pi(\mathbf{x} \mid \boldsymbol{\theta}) \prod_{i,t} \pi(y_{i,t} \mid x_{i,t}, \boldsymbol{\theta}), \tag{10}$$

where $\pi(\boldsymbol{\theta})$ and $\pi(\mathbf{x} \mid \boldsymbol{\theta})$ denote the priors for hyperparameters and the latent field, respectively. MCMC generated a sequence of samples $\{(\mathbf{x}^{(s)}, \boldsymbol{\theta}^{(s)})\}_{s=1}^{S}$ by constructing a Markov chain with the posterior as its stationary distribution.

The latent field components were updated via Gibbs sampling, while the remaining parameters were updated using Metropolis or Metropolis-Hastings steps. Marginal posterior distributions were approximated empirically as

$$\begin{aligned}
\pi(x_j \mid \mathbf{y}) &\approx \frac{1}{S}\sum_{s=1}^{S} \delta(x_j - x_j^{(s)}), \\
\pi(\theta_k \mid \mathbf{y}) &\approx \frac{1}{S}\sum_{s=1}^{S} \delta(\theta_k - \theta_k^{(s)}),
\end{aligned} \tag{11}$$

and posterior summaries, including means, medians and credible intervals, were computed directly from these samples.

4. Results and Discussions

This section presents the findings of the study, highlighting the spatial and temporal patterns observed in malaria incidence and mortality across Kenya. It uses spatio-temporal random effects models techniques and interprets the results in light of

the study objective.

4.1. Descriptive Statistics

Descriptive statistics were presented to offer an initial understanding of trends and variability of malaria incidence and mortality ratio thus setting the stage for subsequent spatio-temporal modeling. Table 1 presents a summary of malaria incidence, mortality and incidence mortality rates across Kenyan counties, highlighting clear spatial differences.

Table 1. *Summary Statistics for Study Data.*

Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
IR	2.0	226.5	397.0	645.5	720.5	3668.0
MR	0.0	29.5	64.0	96.78	121.0	760.0
IMR	1.0	5.0	7.0	8.53	10.0	48.0

Malaria incidence ranged from 2.0 to 3,668.0 per 10,000 people, with an average of 645.5, indicating that certain regions experienced a much higher disease burden than others. Mortality rates showed a similar trend, varying between 0.0 and 760.0 with an average of 96.78 suggesting that malaria-related deaths remained a concern in some areas despite ongoing control initiatives. The incidence mortality rate (IMR) also varied notably, from 1.0 to 48.0 with an average of 8.53.

Figure 1 presents the temporal distribution of malaria incidence mortality ratio in Kenya from 2010 to 2022. The incidence mortality ratio exhibited substantial variability in the early years, with notably higher medians and wider inter-quartile ranges in 2011 and 2012, suggesting significant fluctuations in disease burden and reporting during that period. From 2013 onward, the ratio stabilized at lower levels, indicating greater consistency across regions. However, a gradual increase in variability was observed between 2018 and 2020, marked by several high outliers, before a slight resurgence in 2022.

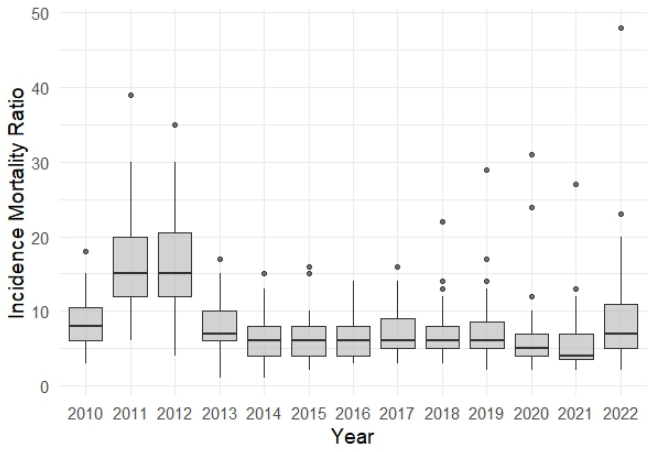

Figure 1. *Yearly distribution of the malaria incidence mortality ratio in Kenya from 2010 to 2022.*

Figure 2 gives the Spatial Distribution of the malaria incidence mortality ratio in Kenya.

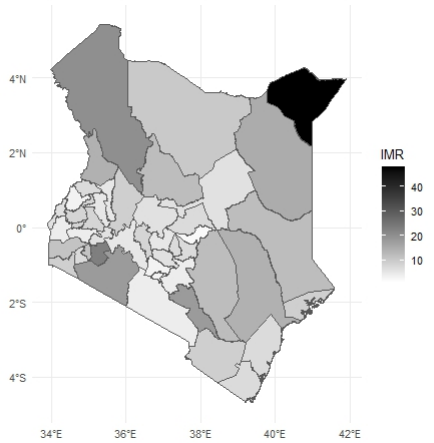

Figure 2. *Spatial Distribution of the malaria incidence mortality ratio in Kenya.*

Notably, the northeastern region, particularly Mandera County, exhibited the highest Incidence Mortality Ratio, suggesting significant disparities in malaria incidence and mortality across the country. Central and some western counties appeared lighter, indicating relatively lower Incidence Mortality Ratios.

4.2. Spatio-temporal Random Effects Model Results

In order to determine the best spatio temporal random effects model to use in the modeling of malaria incidence and mortality, this study considered the Poisson Spatio-Temporal Linear Trend Model (PSTLM), the Poisson Spatio-Temporal ANOVA Model (PSTAM), the Poisson Spatio-Temporal Separable Model (PSTSM) and the Poisson Temporal Model for Spatio-Temporal Effects (PTSTN) to model malaria incidence morality ratios.

Table 2 presents the posterior summaries of the Spatio-Temporal Poisson Conditional Autoregressive models. The Poisson Spatio-Temporal Linear Trend Model (PSTLM) exhibited a strong intercept (mean = 6.4503, 95% CI: 6.4311; 6.4695) and a negative temporal trend ($\alpha = -0.3938$), accompanied by moderate spatial heterogeneity ($\tau^2_{int} = 0.2004$, $\tau^2_{slo} = 17.2281$) and weak spatial dependence ($\rho_{int} = 0.1189$, $\rho_{slo} = 0.1438$). The Poisson Spatio-Temporal ANOVA Model (PSTAM) recorded a slightly higher baseline mean (6.5321) with greater spatial variance ($\tau^2_S = 11.0506$) relative to temporal variance ($\tau^2_T = 2.5036$).

The interaction component ($\tau^2_I = 4.4182$) and mild spatial-temporal dependence ($\rho_S = 0.1736$, $\rho_T = 0.2114$) reflected moderate spatial-temporal variability across the study area. The Poisson Separable Spatio-Temporal Model (PSTSM) produced consistent baseline estimates (mean = 6.4982) and low spatial ($\rho_S = 0.0290$) and temporal ($\rho_T = 0.0984$) correlations, indicating weak dependence between spatial units and time periods.

Table 2. *Posterior summaries for spatio-temporal Poisson CAR models.*

Parameter	Mean	95%CI_low	95%CI_upp
Poisson Spatio-Temporal Linear Trend Model (PSTLM)			
Intercept	6.4503	6.4311	6.4695
α	-0.3938	-0.4145	-0.3762
τ^2_{int}	0.2004	0.0796	0.3291
τ^2_{slo}	17.2281	2.4358	43.6140
ρ_{int}	0.1189	0.0218	0.2091
ρ_{slo}	0.1438	0.0018	0.3807
Poisson Spatio-Temporal ANOVA Model (PSTAM)			
(Intercept)	6.5321	6.4967	6.5674
τ^2_S	11.0506	1.1164	23.4735
τ^2_T	2.5036	0.6712	7.1363
τ^2_I	4.4182	2.8643	6.0308
ρ_S	0.1736	0.0008	0.3513
ρ_T	0.2114	0.0756	0.3551
Poisson Spatio-Temporal ANOVA Model (PSTAM)			
(Intercept)	6.4982	6.4765	6.5199
τ^2_T	0.2495	0.0396	0.9217
ρ_S	0.0290	0.0027	0.0812
ρ_T	0.0984	0.0156	0.2154
Poisson AR1 Temporal Model for Spatio-Temporal Effects			
(Intercept)	6.4818	6.4603	6.5033
ρ_S	0.2025	0.1100	0.2981
ρ_T	0.0109	0.0002	0.0292
Poisson AR2 Temporal Model for Spatio-Temporal Effects			
(Intercept)	6.5042	6.4789	6.5295
ρ_S	0.1678	0.1336	0.2351
$\rho_{1,T}$	-0.1602	-0.2577	-0.0717
$\rho_{2,T}$	-0.0294	-0.1316	0.0806

The Poisson AR1 Temporal Model for Spatio-Temporal Effects (PTSTN-AR1) maintained a comparable intercept (mean = 6.4818) with moderate spatial correlation ($\rho_S = 0.2025$) and minimal temporal correlation ($\rho_T = 0.0109$), representing a simple autoregressive structure that captured short-term variation in the data. The Poisson AR2 Temporal Model for Spatio-Temporal Effects Model (PTSTN-AR2) yielded a stable intercept (mean = 6.5042) and modest spatial dependence ($\rho_S = 0.1678$). The first-order temporal parameter ($\rho_{1,T} = -0.1602$) and the second-order parameter ($\rho_{2,T} = -0.0294$) together described short-term fluctuations and limited long-term temporal dependence in the model, providing a higher-order temporal representation of the spatio-temporal process.

4.3. Spatio-temporal Random Effects Model Evaluation

Table 3 presents the model fit statistics for the spatio-temporal Poisson CAR models, evaluated using the Deviance Information Criterion (DIC), the effective number of parameters ($p.d$) and the Log Marginal Pseudo-Likelihood (LMPL). Among the models, the Poisson Spatio-Temporal ANOVA Model (STPAM) achieved the lowest DIC (245,746.0) and the highest LMPL (-136,563.7), indicating the best overall fit and balance between model complexity and accuracy. The linear trend model (STPLM) and the autoregressive models (PTSTN-AR1 and PTSTN-AR2) demonstrated moderate performance, while the separable model (STPSM) showed the weakest fit. The STPAM model provided the most effective representation of the spatio-temporal structure in the data.

Table 3. *Model fit statistics for spatio-temporal Poisson CAR models.*

Model	DIC	p.d	LMPL
STPLM	465,143.6	2,666.9	-246,518.7
STPAM	245,746.0	2,168.9	-136,563.7
STPSM	564,256.8	3,106.9	-289,732.0
PTSTN-AR1	526,386.0	3,133.7	-285,500.8
PTSTN-AR2	547,110.4	3,182.3	-285,189.3

4.4. Poisson Spatio-Temporal ANOVA Model Results

Figure 2 depicts the temporal trend of the average malaria incidence and mortality ratio (IMR) in Kenya from 2010 to 2022. The trend exhibited intermittent peaks in 2012 and 2019, corresponding to periods of heightened malaria burden, followed by short-term declines. Although fluctuations were evident, the overall pattern remained relatively stable without

a sustained upward or downward trajectory. The broader variability bands in 2012, 2016 and 2019 reflected increased regional disparities, highlighting the uneven and dynamic nature of malaria transmission across the country.

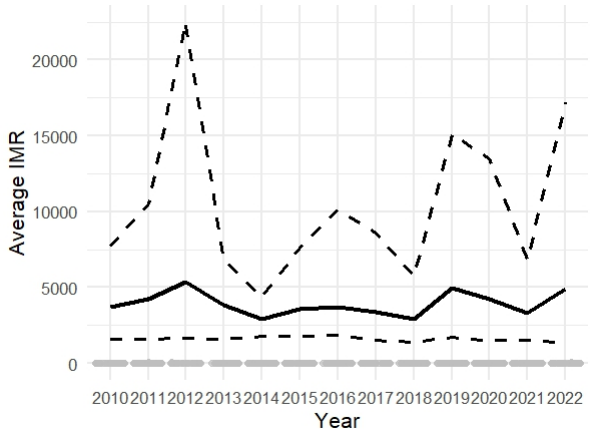

Figure 3. *Temporal trend of the average malaria incidence and mortality ratio (IMR) in Kenya from 2010 to 2022.*

Figure 3 shows the spatial distribution of mean malaria rates across Kenyan counties, revealing strong spatial heterogeneity. Higher rates occurred in coastal and northeastern counties, moderate rates in central and western areas and lower rates in highland and arid northern zones.

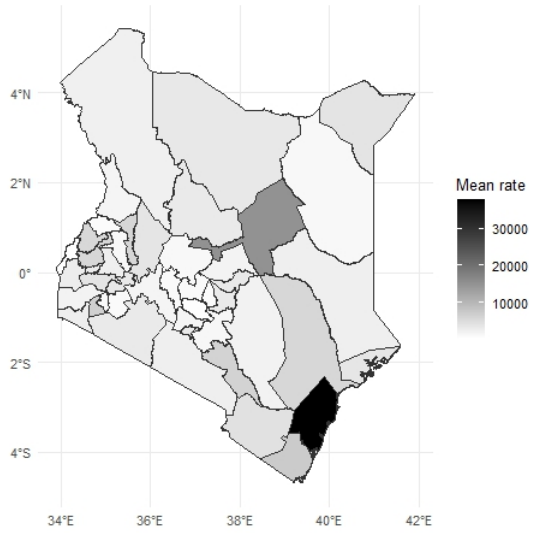

Figure 4. *Spatial distribution of mean malaria rates across Kenyan counties.*

Figure 4 presents the exceedance probability map for malaria incidence across Kenyan counties, indicating areas where malaria risk surpasses a defined threshold. High probabilities were concentrated in coastal, northeastern and western counties, highlighting persistent transmission hotspots. In contrast, central and northern arid counties exhibited lower probabilities, suggesting reduced risk.

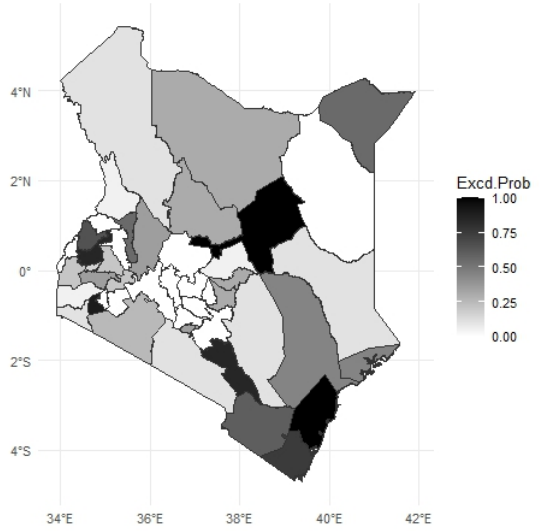

Figure 5. *Exceedance probability map for malaria incidence across Kenyan counties.*

4.5. Poisson Multivariate Spatio-Temporal Areal Model Results

Table 4 gives Posterior summaries of Poisson Multivariate Spatio-Temporal Areal Model parameters. The baseline log-counts for malaria incidence and mortality were 6.47 and 4.57, respectively, suggesting higher expected values for Malaria Incidence relative to Malaria Mortality. The estimated marginal variances, $\Sigma_{11} \approx 8.02$ and $\Sigma_{22} \approx 18.70$, revealed substantial variability in both outcomes not accounted for by the fixed effects, with Malaria Mortality exhibiting greater uncertainty.

Table 4. *Posterior summaries of the PMVST model parameters.*

Parameter	Mean	2.5%	97.5%
Incidence (Intercept)	6.4695	6.4695	6.4695
Mortality (Intercept)	4.5661	4.5661	4.5661
Σ_{11}	8.0196	5.1272	17.3960
Σ_{22}	18.7047	8.5334	46.9938
ρ_S	0.0932	0.0633	0.1859
$\rho_{1,T}$	-0.0789	-0.1545	0.0004
$\rho_{2,T}$	-0.0309	-0.0944	0.0347
DIC = 63, 841.71, p.d. = 2, 507.73, LMPL = -1, 467.4			

The spatial correlation parameter ($\rho_S \approx 0.093$) suggested modest positive spatial dependence among neighboring counties, while the temporal autoregressive parameters ($\rho_{1,T} \approx -0.079$; $\rho_{2,T} \approx -0.031$) indicated slight negative temporal autocorrelation for malaria incidence and mortality. The proposed model captured notable variability in the multivariate modeling of malaria incidence and mortality with weak to moderate spatial and temporal dependence. The lower Deviance Information Criterion value of 63, 841.71 and higher Log Marginal Pseudo-Likelihood value of -1467.4 provided baseline measures for model fit in comparison to the univariate Spatio-Temporal Poisson ANOVA Model (STPAM). These

results indicated that the Poisson Multivariate Spatio-Temporal Areal Model is a model of choice in the joint modeling of malaria incidence and mortality in Kenya in comparison to the univariate Spatio-Temporal Poisson ANOVA Model.

Figure 6 presents the Poisson Multivariate Spatio-Temporal temporal trends in average malaria incidence and mortality in Kenya between 2010 and 2022. The figure revealed marked inter-annual fluctuations, characterized by sharp peaks in 2011 and 2017, followed by notable declines, suggesting intermittent surges in malaria transmission.

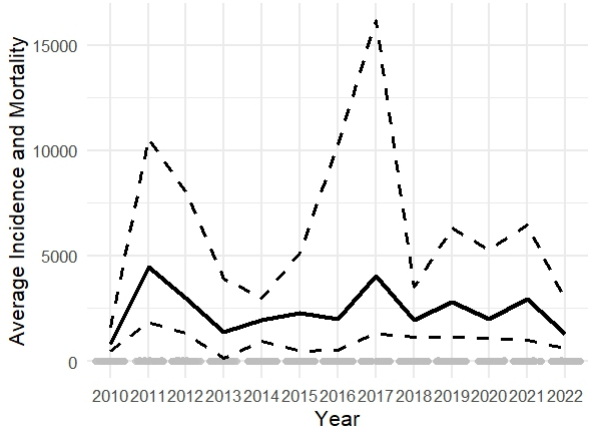

Figure 6. *Multivariate Temporal Trend for malaria incidence and mortality in Kenya.*

Figure 7 depicts the Poisson Multivariate Spatio-Temporal spatial distribution of malaria spatio-temporal effects across Kenyan counties, highlighting notable regional disparities in malaria burden.

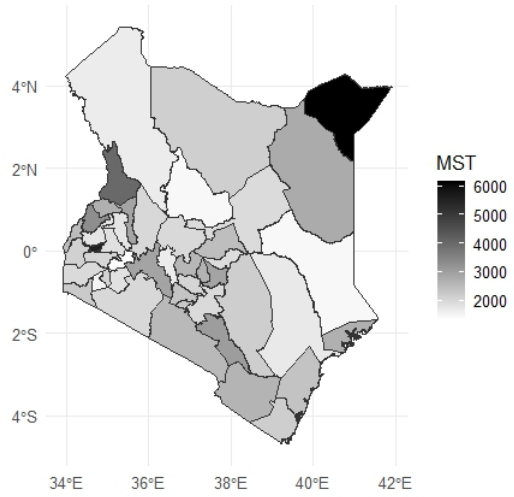

Figure 7. *Multivariate Spatial Trend for malaria incidence and mortality in Kenya.*

From Figure 7, the Lake Victoria basin and parts of North Eastern Kenya emerged as hotspots, reflecting ecological and climatic conditions favorable for mosquito breeding and sustained malaria transmission as also given by [20, 21, 30].

Figure 8 shows the probability that malaria risk exceeds the national average across different counties in Kenya, highlighting clear spatial variations in disease burden. The western and north-eastern parts of the country had a higher likelihood of elevated malaria risk, suggesting these areas experience persistent transmission. This pattern aligns with regions known for favorable mosquito breeding conditions, such as proximity to water bodies and humid climates, as well as areas where access to malaria control interventions may be limited.

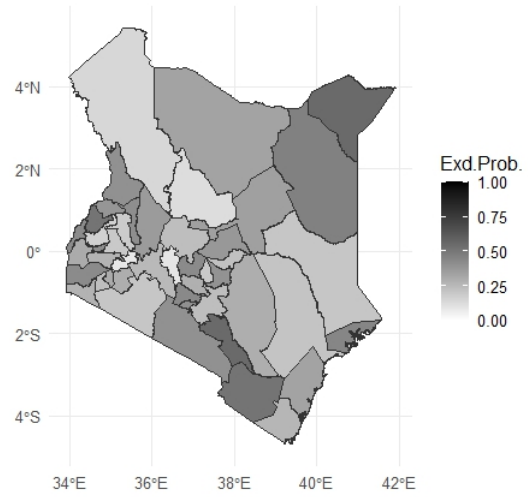

Figure 8. *Multivariate Exceedance Probability for malaria incidence and mortality in Kenya.*

5. Conclusion and Recommendations

This section gives a summary the main findings of the study and presents recommendations for malaria incidence and mortality modeling.

5.1. Conclusion

This study has demonstrated the utility of spatio-temporal random effects modeling in capturing the spatial and temporal dynamics of malaria incidence and mortality in Kenya. By integrating spatially structured random effects with auto-regressive temporal components, the proposed Poisson Multivariate Spatio-Temporal Areal Model effectively quantified both spatial heterogeneity and temporal dependence, providing robust insights into the distribution and persistence of malaria incidence and mortality risk. The results revealed significant regional disparities in malaria incidence and mortality transmission, reflecting the influence of environmental, demographic and socioeconomic factors across the Kenyan Counties.

Beyond mapping malaria incidence and mortality patterns, this research contributed to methodological advancements in malaria epidemiology by applying a hierarchical Bayesian approach that accommodated uncertainty and data sparsity

across sub-national regions. The findings affirm that spatially explicit, temporally dynamic analyses are critical for malaria surveillance and control, particularly in endemic countries experiencing heterogeneous transmission patterns as with the case of Kenya. Ultimately, this work advanced the empirical understanding of malaria epidemiology while offering a spatial-temporal foundation for targeted intervention design and monitoring within Kenya's malaria elimination agenda at the sub-national levels .

5.2. Recommendations

Future research can extend the current modeling framework by incorporating ecological and behavioral covariates that capture vector and human interactions and intervention coverage dynamics. Another important direction for future studies would be the exploration of nonlinear spatio-temporal processes with non-stationary covariance structure aimed at capturing more complex malaria incidence and mortality dynamics. Additionally, the joint modeling of malaria with co-morbid diseases such as anemia or respiratory infections can uncover shared spatial risk factors relevant to integrated disease management.

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Abbreviations

ANOVA	Analysis of Variance.
CAR	Conditional Auto-regression Model.
DIC	Deviance Information Criterion.
INLA	Integrated Nested Laplace Approximation.
IR	Incidence Rate.
IMR	Incidence Mortality Rate.
LMPL	Log Marginal Pseudo-Likelihood.
MR	Mortality Rate.
PTSTN	Poisson Temporal Model for Spatio-Temporal Effects.
STPLM	Spatio Temporal Poisson Linear Trend Model.
STPAM	Spatio Temporal Poisson Anova Model.
STPSM	Spatio Temporal Poisson Separable Model.

Conflict of Interest

The authors declare no conflicts of interest.

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