Comparing malaria vector species composition trends in sites implementing Indoor Residual Spraying (IRS) and Long-Lasting Insecticidal Nets (LLINs) as core vector control interventions.

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Outlines

1. Introduction
2. Objectives
3. Methodology
4. Model Component
5. Results
6. Conclusion & Recommendation
7. References

General Introduction

Malaria remains one of the most significant global public health problems, particularly in Sub- Saharan Africa (Oladipo, 2022).

Introduction: Malaria in the world

- **Global Malaria Burden**: The estimated number of global malaria cases in 2022 surpassed pre-pandemic levels from 2019. According to the WHO's 2023 World Malaria Report, 249 million cases were reported globally across 85 malaria-endemic countries, with a case incidence of 58 per 1000 population at risk in 2022. This is higher than the 233 million cases recorded in 2019, indicating a growing challenge.

- **Global Mortality Rates**: Malaria continues to have a significant global mortality rate. In 2022, 608,000 deaths were reported, translating to 14.3 deaths per 100,000 population at risk. These figures underline the persistent global burden of malaria.

(The 2023 WHO World malaria report)

Introduction: Malaria in the Africa

- **Malaria Burden in Africa**: Africa remains the region most heavily affected by malaria, accounting for 94% of global cases in 2022. Out of the 249 million malaria cases reported globally, 94% of 249 million were concentrated in the WHO African Region. This underscores the significant and persistent malaria burden on the continent.

- **High-Burden Countries**: A few countries bear the brunt of the malaria epidemic in Africa. Nigeria alone accounted for 27% of global cases in 2022, followed by the Democratic Republic of the Congo (12%), Uganda (5%), and Mozambique (4%). These four countries together contribute nearly half of all malaria cases worldwide.

- **Malaria Mortality in Africa**: More than 50% of global malaria deaths occurred in just four African nations: Nigeria (31%), the Democratic Republic of the Congo (12%), Niger (6%), and Tanzania (4%). This highlights the deadly toll malaria continues to take on the African population, especially in countries with limited healthcare access and resources.

(The 2023 WHO World malaria report)

Introduction: Malaria in the Rwanda

- **Public Health Concern**: Malaria is a leading cause of morbidity and mortality in Rwanda, remaining a major public health issue.
- **Population at Risk**: The entire population of 12.9 million is at risk of malaria, with pregnant women, children under five, and refugees being the most vulnerable groups.
- **Global Malaria Burden**: In 2021, Rwanda accounted for 1.2% of global malaria cases, reflecting the continued challenge of controlling the disease.
- **Reduction in Malaria Cases**: Between 2020 and 2021, malaria incidence in Rwanda decreased by 44%, dropping from 227 to 126 cases per 1000 population at risk.
- **Mortality Rate**: Malaria-related deaths remained steady at 0.244 per 1000 population at risk during the same period.

(Severe Malaria Observatory)

Some of vectors Contributing to the Malaria Burden

The malaria burden is largely driven by three primary mosquito species:

- **Anopheles gambiae**: Known for its high efficiency in malaria transmission due to its preference for human hosts.
- **Anopheles arabiensis**: Adapted to drier regions, this vector shows a tendency for outdoor biting and early feeding.
- **Anopheles funestus**: A competent vector that breeds in permanent water sources like swamps, making it a persistent threat year-round.

These three species are the key vectors responsible for the ongoing transmission of malaria.

(Karema, 2020)

Core Malaria Vectors Control

In the context of malaria prevention, the two primary core vector control interventions are Long-Lasting Insecticidal Nets (LLINs) and Indoor Residual Spraying (IRS).

1. **Long-Lasting Insecticide-Treated Nets (LLINs)** These are mosquito nets treated with an insecticide that is intended to kill or repel mosquitoes. the distribution of LLINs is a critical intervention to provide a physical barrier that protects people from mosquito bites during the night when mosquitos are most active.

2. **Indoor Residual Spraying (IRS)**
   IRS involves spraying the interior walls of homes with insecticides. Mosquitoes that come into contact with the treated walls are killed or repelled

(RWANDA INTEGRATED MALARIA CONTROL GUIDELINES, Edition 2024)

Objectives

Main objective

The primary objective of this study is to investigate the dynamics of malaria vector species composition in response to Indoor Residual Spraying (IRS) and Long-Lasting Insecticidal Nets (LLINs). Specifically, the study aims to:

1. **Understand Patterns in Vector Composition Before and After Interventions**
   - To determine the patterns in vector species composition before and after the implementation of IRS and LLIN interventions.
2. **Develop a Statistical Model to Capture Changes in Species Composition**
   - To build a model capable of capturing changes in the species composition of malaria vectors over intervention.

Problem statement

- This study aims to investigate the dynamics of vector species composition , focusing specifically on the impact of IRS and LLINs.
- By examining how these interventions influence mosquito populations, we can identify potential gaps in current control strategies.

Methodology: Data needed

- The data collection phase of this study will involve compiling existing intervention information and vector sampling data that are readily available.
- This includes gathering details on the types and specifics of control measures already implemented, as well as accessing records related to mosquito populations and their behaviors.
- These are columns in the dataset collated and published by (Massey, 2016)

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Data Processing

Data processing is a critical step in ensuring that the dataset is of high quality, clean, and ready for analysis. This section outlines the key processes undertaken to clean and transform the dataset.

- Cleaning
  - Consistency in Data Formats: for example, discrepancies in the recording of species names (e.g., different formats of gambiae ss) were standardized
- Transformation
  - Feature Creation: Ex: POST INTERVENTION flag helped in distinguishing baseline data from post-intervention data, making it easier to analyze the impact of interventions.

Statistical Modeling

- The core of this study is the development and implementation of a Poisson Generalized Linear Model (GLM).
- **Generalized Linear Models (GAMs)**. Generalized Linear Models (GLMs) were introduced by (Nelder and Wedderburn, 1972)
- A key advantage of GLMs is their ability to model the relationship between dependent and independent variables through a linear predictor while allowing for the response variable to follow a distribution other than normal

Poisson GLM structure

For a Poisson GLM, the link function typically used is the logarithm, which models the log of the expected count as a linear combination of the predictors:

$$\log(E(Y)) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p$$

This formulation allows the expected counts to be expressed in terms of the independent variables, thereby providing a direct interpretation of the effects of predictors on the response variable. The coefficients $\beta_1, \ldots, \beta_p$ indicate the change in the log count of the response variable for a one-unit change in the corresponding predictor (Hilbe, 2009).

Since we have part of random effect, we extend our model to mixed-effects poisson regression model (Matthew J. Silk, 2020)

Model Components

Mixed-effects poisson regression model Structure for This Study:

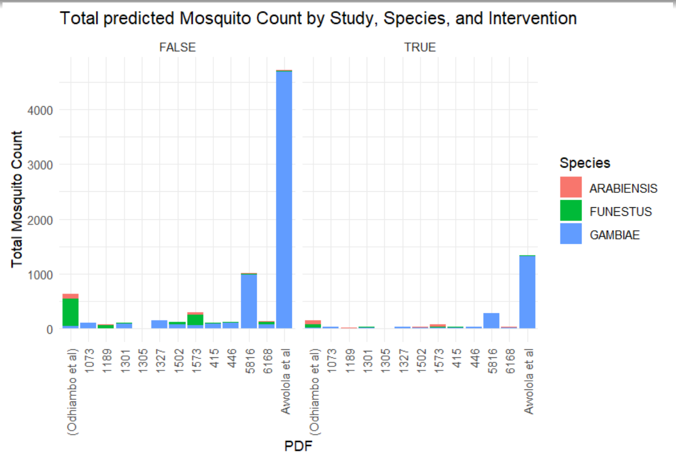
$$\log(\text{COUNT}_{ij}) = \text{offset}(\log(\text{NSAMP}_{ij})) + u_{ID_i} + v_{SAMPLING_j} + w_{PDF_k}^{(SPECIES)} + \beta_1 \cdot \text{POST\_INTERVENTION}_{ij} + \beta_2 \cdot (\text{SPECIES}_{ij} \cdot \text{POST\_INTERVENTION}_{ij})$$

Model Components

Where:

- $\log(\text{COUNT}_{ij})$ is the log of the expected mosquito count for study i and sampling method j.
- $\text{offset}(\log(\text{NSAMP}_{ij}))$ is the offset term that adjusts for the number of samples (NSAMP) in study i and method j.
- u_{ID_i} is the random intercept for the clusters to account for differences in average abundance across clusters.
- $v_{SAMPLING_j}$ is the random intercept for the different sampling methods, accounting for differences in catch rates due to the methods used.
- $w^{(SPECIES)}_{PDF_k}$ is the random slope for species within each study, allowing the effect of species to vary across studies k.
- $\beta_1 \cdot \text{POST\_INTERVENTION}_{ij}$ is the fixed effect for the post-intervention period, modeling the average effect of the intervention on mosquito catch rates.
- $\beta_2 \cdot (\text{SPECIES}_{ij} \cdot \text{POST\_INTERVENTION}_{ij})$ is the interaction term between species and the post-intervention period, capturing how the intervention affects different species differently.

Results:Patterns in Vector Composition Before and After In- terventions



- The graph indicates that interventions significantly reduce populations of mosquito species (Arabiensis, Funestus, and Gambiae) across studies, with a marked decrease in species counts when interventions are applied.

Results: Summary of Statistical Models

Table: Random effects:

Groups	Name	Std.Dev.
ID	(Intercept)	1.14493
PDF	(Intercept)	1.76281
	SPECIESfunestus	0.07652
	SPECIESgambiae	3.93946
SAMPLING	(Intercept)	0.68755

Table: Summary of Fixed Effects

Term	Estimate	Std. Error	z value	$Pr(>\|z\|)$
POST_INTERVENTIONFALSE	1.3722	0.8965	1.531	0.126
POST_INTERVENTIONTRUE	1.3139	0.8964	1.466	0.143
POST_INTERVENTIONFALSE:SPECIES_funestus	1.6238	0.2632	6.169	6.86e-10 ***
POST_INTERVENTIONTRUE:SPECIES_funestus	-0.4204	0.2640	-1.593	0.111
POST_INTERVENTIONFALSE:SPECIES_gambiae	3.1396	1.9240	1.632	0.103
POST_INTERVENTIONTRUE:SPECIES_gambiae	1.9381	1.9241	1.007	0.314

Assumptions

- This project would respond to Rwanda's situation if The data were collected in Rwanda or any other country with similar climatic conditions and vector control interventuon

Conclusion

- The mixed-effects poisson regression model shows effects on malaria vector populations, especially An. gambiae, An. funestus, and An. arabiensis.
- An. funestus has higher abundance pre-intervention compared to An. arabiensis but decreases post-intervention, though not significantly.
- An. gambiae exhibits higher pre-intervention abundance, with no statistically significant effects from the intervention.

Recommendations

- Conducting long-term studies that monitor mosquito populations over multiple seasons may provide deeper insights into the temporal dynamics of species abundance and the potential lag effects of interventions.

- Assessing environmental variables that influ- ence mosquito behavior and habitat preferences may offer additional explanations for the observed patterns. Understanding these factors can guide more effective interventions.

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