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Geospatial and Path Analysis for Enhancing Malaria Control and Primary Healthcare Delivery in Low-Income Nations: A Case Study of Uganda

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Abstract This research investigated the use of Geospatial and Path Analysis for Enhancing Malaria Control and Primary Healthcare Delivery in Low-Income Nations. Utilizing methods such as generalized linear regression (GLR), ordinary least squares (OLS) regression, and spatial autocorrelation (Moran's I), the study identified key factors influencing malaria incidence rates: mean temperature, antimalarial treatment, mosquito net access, total population, and total health centers. The GLR and OLS analyses showed a moderate model fit (Adjusted $R^2 = 0.443$), highlighting the importance of these predictors. Path analysis was used to determine both the direct and indirect effects of these variables on malaria incidence rates, leading to the creation of a new model. In this model, mean temperature showed a significant direct effect ($\beta = 0.658$) and a small indirect effect ($\beta = 0.002779$), resulting in a total effect of 0.660779. Antimalarial treatment had a strong negative direct effect ($\beta = -0.189$) with a negligible indirect effect, yielding a total effect of -0.18947. Mosquito net access demonstrated a notable direct effect ($\beta = 0.074$) and a substantial indirect effect ($\beta = 2.5214437$), culminating in a total effect of 2.59544. Total population exhibited a small direct effect ($\beta = -0.180$) and a minimal indirect effect ($\beta = -0.0001927$), leading to a total effect of -0.18019. Finally, the number of health centers showed no direct effect but a significant indirect effect ($\beta = 1.0956237$), resulting in a total effect of 1.0956237. Spatial autocorrelation revealed significant clustering of malaria rates, highlighting the need for targeted interventions. Bivariate color maps underscored the critical role of health centers in improving healthcare access and controlling malaria, suggesting that expanding health center networks in underserved regions could enhance healthcare outcomes

Keywords: *Geospatial analysis, path analysis, primary healthcare, malaria, Low-income nations, Universal Health Coverage (UHC), Uganda*

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1. Introduction

Many studies have examined the geographic, socio-demographic, and epidemiological factors that shape malaria dynamics. However, none have emphasized or employed path analysis to understand the direct and indirect influences on malaria. This study addresses this gap, highlighting the critical need for employing path analysis in malaria research to develop more effective control strategies. Path analysis is a statistical technique used to develop and test theoretical models by quantifying hypothesized causal relationships among variables. It is crucial for understanding the direct and indirect effects of various factors on healthcare outcomes, such as malaria incidence rates. By distinguishing between direct impacts (e.g., mean temperature, antimalarial treatment) and indirect impacts (e.g., total population, healthcare infrastructure), path analysis provides a comprehensive view of the interactions affecting health. Furthermore, the need for this study is paramount in the context of Uganda, where malaria remains a significant public health challenge. By employing path analysis, we can uncover critical insights that traditional methods may overlook, thereby enabling more precise and impactful interventions. This study's findings could be transformative, enhancing the effectiveness of malaria control programs and reducing the disease's burden on affected populations.

Similarly, bivariate color maps are essential for visualizing the spatial relationships between healthcare variables and outcomes. They enable policymakers to identify high-need areas, assess the effectiveness of current healthcare infrastructure, and make informed decisions about resource allocation and intervention strategies. Utilizing these analytical tools allows for a more targeted approach to improving healthcare delivery and outreach programs in Uganda, ensuring that interventions are both equitable and effective.

Given the ongoing struggle against malaria in Uganda and similar regions, this study's findings are crucial. By providing a deeper understanding of the dynamics at play, we can enhance the effectiveness of malaria control programs and ultimately reduce the disease's burden on affected populations. This research underscores the need for innovative analytical approaches to tackle persistent healthcare challenges in low-income nations [1].

This research underscores the need to address healthcare disparities for achieving universal health coverage (UHC) and reducing health inequities through innovative solutions using geospatial analysis and path analysis techniques. Health inequality is a global concern, affecting diverse social strata, with developed countries facing disparities linked to income and socio-economic factors [2]. In low-income nations, especially rural Sub-Saharan Africa (SSA), significant healthcare disparities persist, hindering progress towards UHC. Challenges in aligning healthcare supply with demand persist, disproportionately affecting rural areas and contributing to extended travel times, limited facilities, and high poverty rates [3].

2. Materials and Methods

Uganda's healthcare system faces criticism for perceived inequities, with geographic barriers impacting access [4]. Geospatial analysis identifies high healthcare needs areas, optimizing resource allocation, while AI-driven algorithms predict disease outbreaks, aid decision-making, and support telemedicine for improved access. These technologies aim to enhance primary healthcare, reduce disparities, and align with UHC principles [5].

Over the years, a significant rise in both indoor and outdoor temperatures across various types of roofing has been observed, underscoring the impacts of global warming. This increase in temperature, particularly notable in tropical countries like Uganda, has been linked to an elevated risk of malaria transmission [6].

Malaria remains a major global public health challenge, affecting millions, especially in endemic regions such as Uganda. The complex interplay between climate change and malaria dynamics is of growing concern. Climate change, characterized by alterations in temperature, rainfall, and weather patterns, significantly influences malaria transmission. Both the development of the Plasmodium parasite within the mosquito vector and the maturation of the mosquito are temperature-dependent processes. As global temperatures continue to rise, the geographic range of malaria is likely to expand, rendering previously malaria-free areas susceptible to transmission. This scenario emphasizes the urgent need to integrate climate considerations into malaria control and prevention strategies [7].

The relationship between temperature and malaria transmission has been the focus of numerous studies due to the profound implications of climate change on disease dynamics. Recent research by [8] provides valuable insights into this relationship. Published in Nature Communications, their study examines the impact of temperature on the transmission of Plasmodium falciparum by the mosquito Anopheles gambiae. The study found that optimal parasite infection in mosquitoes occurs at temperatures between 23°C and 25°C, whereas extreme temperatures, whether too low or too high, significantly reduce infection rates. These findings highlight the necessity of considering temperature variations and species-specific data to accurately predict malaria transmission dynamics under future climate scenarios.

Uganda's efforts to reduce malaria incidence involve the increased use of indoor residual spraying (IRS), long-lasting insecticidal nets (LLINs), and artemisinin-based combination therapy (ACT). However, despite these measures, malaria cases remain high, with 263 cases per 1,000 persons annually in 2019, down slightly from 283 in 2016. This modest 7.2 percent reduction falls significantly short of the target 50 percent reduction by 2025. In 2020, Uganda had the third highest global burden of malaria cases and deaths, underscoring the persistent challenge of controlling malaria despite increased spending [9].

Collectively, these studies underscore the critical need to address the implications of climate change in the context of malaria control. As temperatures rise, the accelerated development of malaria parasites and the expansion of transmission zones present formidable challenges. Thus, incorporating climate data into predictive models and developing adaptive strategies is essential for effective malaria prevention and control efforts.

Despite numerous studies on malaria distribution in Uganda, many have overlooked critical direct and indirect factors influencing malaria incidence rates and the effectiveness of healthcare distribution across districts. Malaria remains a leading cause of death globally, particularly in Africa, where wet and warm environments facilitate mosquito breeding and malaria transmission, in a study by [10], Antimalarial treatment was identified as the most influential factor, while access to mosquito nets significantly reduced incidence rates. Conversely, higher temperatures were correlated with increased malaria rates. This research addresses gaps in understanding healthcare center accessibility and population distribution by examining direct and indirect factors affecting healthcare service delivery and outreach programs in Uganda. These factors include total population, antimalarial treatment, mosquito net access, the total number of healthcare centers, and mean temperature, all of which impact malaria incidence rates across Ugandan districts.

Effective preventive measures are crucial in combating malaria. One proven strategy is to block mosquito-human contact by using insecticide-treated mosquito nets and implementing measures to block the transmission routes of Anopheles mosquitoes. Another critical approach is the use of antimalarial drugs for case management, with the World Health Organization (WHO) recommending artemisinin-based combination therapies (ACTs) as the first-line treatment for falciparum malaria. However, the preservation of current antimalarials is essential, as widespread and unregulated drug use can lead to antimalarial drug resistance, posing a significant threat to malaria control efforts [11].

Universal health coverage (UHC), proposed by the World Health Organization in 2005, aims to ensure equitable access to health care, crucial for achieving desired health outcomes, especially for impoverished or rural populations. Assessing healthcare access is vital for monitoring UHC progress and future planning, measured both spatially, by examining geographic barriers between populations and healthcare resources, and non-spatially, by considering the utilization of medical services under economic and sociocultural influences. Spatial accessibility is a key indicator for evaluating health equity and informs policy-making and healthcare program development [12].

The study by [13] contributes through a scoping review, showcasing the increasing use of spatial analysis techniques in Sub Saharan Africa emphasizing the necessity for precise estimates at lower national levels. The insights provided by [14] from the African Regional GIS Summit strongly advocate for the use of geospatial analysis. The study by [15] explores determinants of healthcare access in Sub-Saharan Africa, aligning with the research's focus on social and economic determinants.

Geography, particularly in the context of health research at the CDC, involves examining global disparities in location and space, with a focus on understanding the "what," "where," and "why" of natural and human phenomena. Tools like maps, spatial statistics, and geographic information systems (GIS) are used in this exploration. GIS is a computer-based tool that stores, visualizes, and analyzes geographic data. This data can encompass anything tied to a specific Earth location. For example, disease cases, hospital sites, road networks, and more are types of spatial data that can be mapped. GIS data also include descriptive attributes. This technology allows for analysis of various spatial questions, like disease patterns, proximity to healthcare facilities, and optimal locations for services like syringe exchange programs [16].

Modern tools, like geographic information systems (GIS), enable more efficient and rapid decision-making by leveraging geographic information to understand population needs, allocate resources precisely, and ensure efficient access to healthcare and resources. GIS aids in monitoring disease status and allows for visualizing, analyzing, modeling, predicting, and intervening when necessary. Additionally, it plays a crucial role in enhancing maternal and child health by helping countries identify areas of need and target outreach efforts effectively in support of sustainable developm*ent.* [17]

Geographic information systems (GIS) are recommended by Asian Development Bank (ADB) and World Health Organization (WHO) to improve healthcare systems. GIS collects, integrates, and analyzes spatial data from various sources for efficient healthcare service planning. It helps create organized healthcare networks, deploy professionals equitably, and generate informative maps at different levels. GIS supports field surveys, thematic mapping, and simulating health-related scenarios. It is crucial for targeted disease programs, especially in communicable disease control and emergency response, by providing a common operational picture and aiding resource allocation decisions [18].

In our proposed model, we hypothesize that mean temperature, mosquito net access, the total number of health facilities, and antimalarial treatment may directly influence malaria incidence rates, whereas the total population may have an indirect effect on these rates.

Figure 1: a) Exogenous i. Mean Temperature

b) Endogenous i. Antimalaria Treatment ii. Total Population iii. Mosquito Net Access iv. Total Number of Health Centers v. Malaria Incident Rates (the Ultimate Endogenous Variable)

I run a multiple regression on the model using the Ultimate Endogenous Variable (Malaria Incident Rates): a) Use βs as path coefficients for each significant predictor. b) Fill in fill in e = $\sqrt{1-R^2}$

c) Eliminate variables that are not significant.

Proposed Conceptual Model for Healthcare service delivery and outreach programs in Uganda

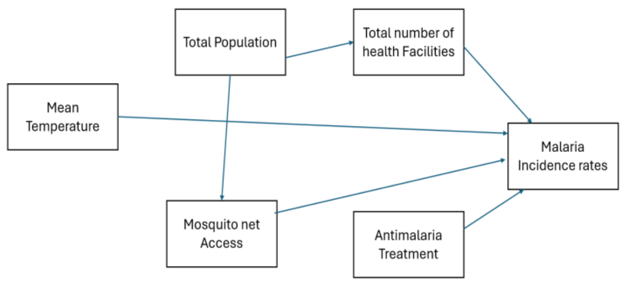


Figure 1

In our research, we employed Gregor, S.'s [19]. Theory Type I1: Explanation to comprehensively understand and address the persistent challenge of malaria transmission in relation to its direct and indirect factors. This theory was applied effectively, integrating both explanatory and predictive components to achieve a deep understanding of malaria transmission dynamics and to inform practical interventions.

The study's objective was to provide detailed explanations of the phenomena related to malaria transmission, including the factors of how, why, when, and where these occurrences took place. By employing path analysis, we achieved a comprehensive understanding of both direct and indirect factors influencing malaria transmission. Additionally, the incorporation of geospatial elements, specifically bivariate color maps, enabled the assessment of relationships among various variables, such as population density, healthcare center locations, access to mosquito nets, availability of antimalarial treatments, mean temperature, and malaria incidence rates. This predictive aspect was essential in developing targeted interventions to control and reduce the impact of malaria.

The adoption of a quantitative research methodology was justified. A non-experimental associational design, in the form of a survey study, was chosen, and a random sampling method was employed to select health facilities from all Ugandan districts. The population included Health Centers IV, III, antimalarial treatment facilities, total population, mean temperature, mosquito net access, and malaria incidence rates. Statistical methods, including Ordinary Least Squares (OLS) regression, generalized linear regression (GLR), and spatial autocorrelation (Moran's I), were used to analyze malaria incidence rates. OLS regression modeled the relationship between malaria incidence and predictor variables such as mean temperature, antimalarial treatment, and mosquito net access, revealing significant predictors and a moderate model fit. GLR provided a more flexible analysis, accommodating non-normal error distributions and addressing spatial autocorrelation, thus enhancing the robustness of the findings. Spatial Autocorrelation analysis using Moran's I indicated a strong positive clustering of malaria incidence rates, with a Moran's Index of 0.999391 and a highly significant p-value, confirming that similar values are spatially clustered. Additionally, bivariate color maps were utilized to visually assess the relationships between total population and other variables, including antimalarial treatment, mosquito net access, mean temperature, total health centers, and malaria incidence rates. This visual method complemented our statistical analyses, providing intuitive insights into spatial relationships and highlighting areas for targeted interventions. Furthermore, a path analysis was conducted to explore the direct and indirect factors affecting healthcare service delivery and outreach programs in Uganda. This analysis considered total population, antimalarial treatment, mosquito net access, total health centers, and mean temperature, all which impact malaria incidence rates across Ugandan districts. Together, these methods offered comprehensive insights into the determinants of malaria incidence and healthcare service distribution, guiding effective intervention strategies.

Data collection

We sourced the dataset from two reputable repositories: the Malaria Atlas Database [20] and the World Bank Climate Change Knowledge Portal [21]. The Malaria Atlas Database provided a comprehensive set of malaria-related information, encompassing incident rates, mosquito net access, mosquito net use rate, antimalarial treatment, and indoor residual spraying. This data was initially presented in a raster format. On the other hand, the World Bank Climate Change Knowledge Portal housed climate data, specifically mean temperature and precipitation, which was conveniently structured in a tabular format. The population data was got from Uganda Bureau of Statistics [22] and health center data was got from the ministry of health [23].

3. Results

Path Analysis model, the dependent variable was Malaria incident rates, in this model, total number of health facilities had no direct relationship with malaria incident rates.

Table 1. Malaria Incidence Rates: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.670ª	.449	.446	.07853	.449	172.945	5	1062	<.001

Table 2. Dependent Variable: Malaria Incidence Rates

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	1.197	.248		4.833	<.001	.711	1.683
	Mean_Temperature	.037	.002	.658	23.155	<.001	.034	.040
	Antimalarial_Treatment	-3.085	.406	-.189	-7.599	<.001	-3.882	-2.289
	Mosquito_Net_Access	.173	.062	.074	2.804	.005	.052	.294
	Total_Population	-4.070	.000	-.180	-6.922	<.001	.000	.000
	Total_Health_Centers	.001	.000	.066	2.411	.016	.000	.002

Table 3. Mean Temperature: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.597 a	.357	.354	1.50520	.357	147.384	4	1063	<.001

Table 4. Dependent Variable: Mean_ Temperature

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	-46.969	4.522		-10.387	<.001	-55.842	-38.096
	Antimalarial_Treatment	97.498	7.184	.337	13.571	<.001	83.401	111.595
	Mosquito_Net_Access	18.198	1.042	.438	17.460	<.001	16.153	20.243
	Total_Population	2.957	.000	.074	2.633	.009	.000	.000
	Total_Health_Centers	-.095	.008	-.335	-12.105	<.001	-.110	-.079

Table 5. Miosqutto Net Access, All Variables Were Directly Correlated: Model Summiary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.504a	.254	.252	.0390474	.254	90.692	4	1063	<.001

Table 6. Dependent Varlable: Mosquito Net_ Access

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
		B	Std. Error	Beta	**t**	**Sig.**	Lower Bound	Upper Bound
1	(Constant)	1.408	.115		12.215	<.001	1.182	1.635
	Antimalarial_Treatment	-1.787	.194	-.256	-9.196	<.001	-2.168	-1.405
	Total_Population	9.703	.000	.100	3.336	<.001	.000	.000
	Total_Health_Centers	.001	.000	.133	4.223	<.001	.000	.001
	Mean_Temperature	.012	.001	.508	17.460	<.001	.011	.014

Malaria incidence rates

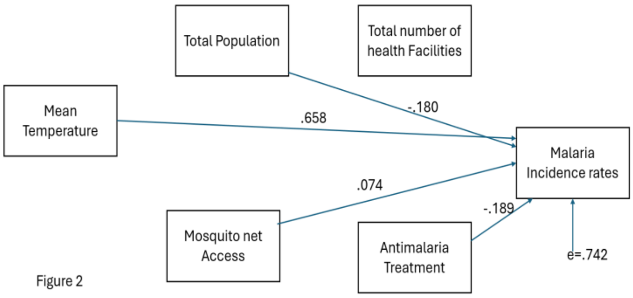


Figure 2

We had to run the next variable which was mean temperature. Total population had no direct effect on mean temperature.

Mean Temperature

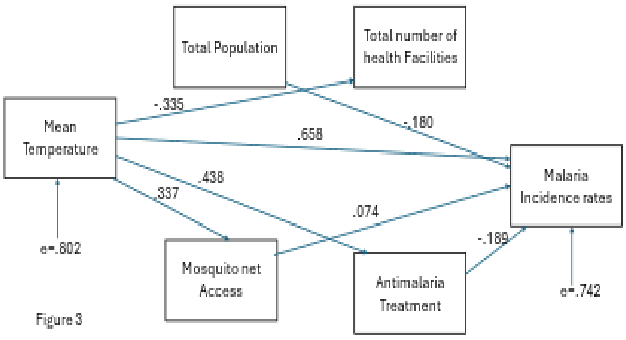


Figure 3

Mosquito net access, all variables were directly correlated

Mosquito net Access

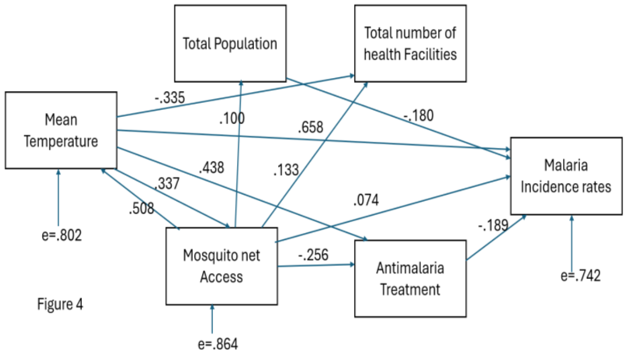


Figure 4

There was no significant relationship between population and Mean temperature

Total population

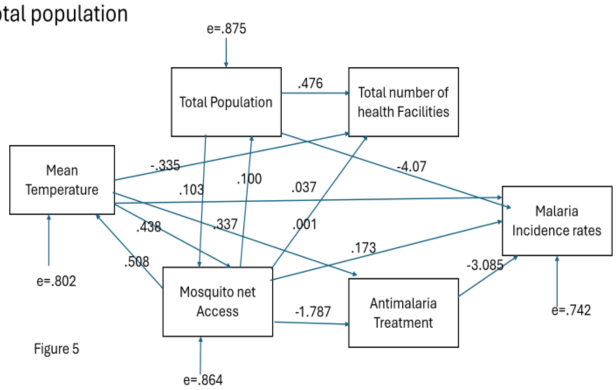


Figure 5

Antimalaria treatment, all variables were directly related

Table 7. Total Population: Model Sumdmiary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.484a	.234	.231	409686.140	.234	81.144	4	1063	<.001

Table 8. Dependent Variable: Total _Population

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	2538046.134	1289418.069		1.968	.049	7952.371	5068139.897
	Antimalarial_Treatment	-6020473.194	2109996.421	-.083	-2.853	.004	-10160704.289	-1880242.099
	Total_Health_Centers	33606.395	2027.153	.476	16.578	<.001	29628.719	37584.072
	Mean_Temperature	21908.953	8321.083	.088	2.633	.009	5581.340	38236.566
	Mosquito_Net_Access	1068076.199	320132.915	.103	3.336	<.001	439911.982	1696240.415

Table 9. Antimalaria Treatment, All Variables Were Directly Related:Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.406ª	.165	.161	.005932614865	.165	52.360	4	1063	<.001

Table 10. Dependent Variable: Antimalarial Treatmient

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
		B	Std. Error	Beta	**t**	**Sig.**	Lower Bound	Upper Bound
1	(Constant)	.602	.003		205.243	.000	.597	.608
	Total_Health_Centers	.000	.000	.206	6.248	<.001	.000	.000
	Mean_Temperature	.002	.000	.438	13.571	<.001	.001	.002
	Mosquito_Net_Access	-.041	.004	-.287	-9.196	<.001	-.050	-.032
	Total_Population	-1.262	.000	-.091	-2.853	.004	.000	.000

Table 11. Total Number of Health Facilities Model Summary

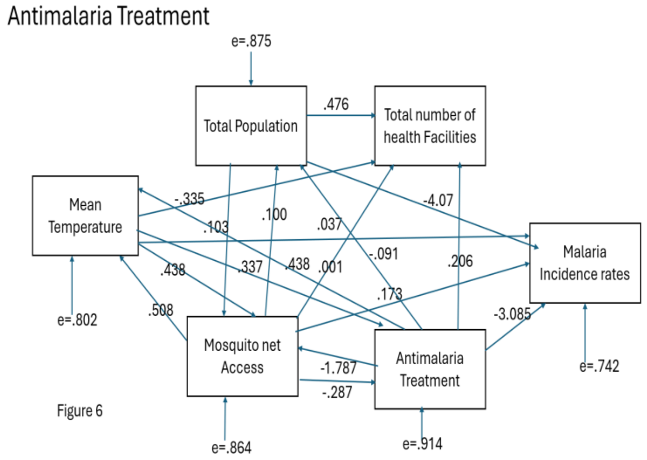
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.552 a	.305	.302	5.525	.305	116.514	4	1063	<.001

Table 12. Dependent Variable: Total Health Centers

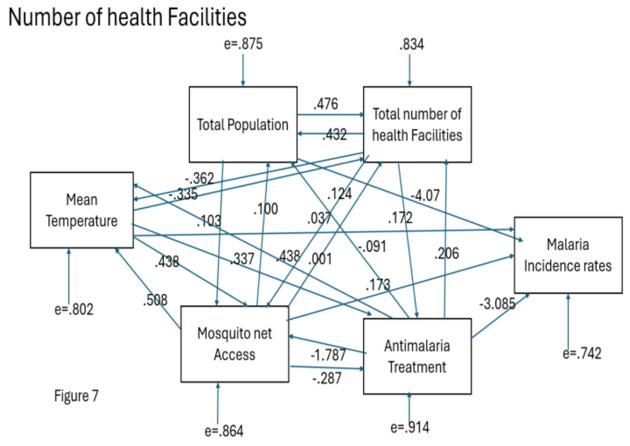
Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
		B	Std. Error	Beta	**t**	**Sig.**	Lower Bound	Upper Bound
1	(Constant)	-79.154	17.252		-4.588	<.001	-113.006	-45.302
	Mean_Temperature	-1.278	.106	-.362	-12.105	<.001	-1.485	-1.071
	Mosquito_Net_Access	18.178	4.304	.124	4.223	<.001	9.733	26.624
	Total_Population	6.113	.000	.432	16.578	<.001	.000	.000
	Antimalarial_Treatment	175.290	28.056	.172	6.248	<.001	120.240	230.341

Table 13. Decomposition Table

Variable	*Direct Effect (Beta)*	*Indirect Effect (Beta)*	*Total Effect (Beta)*
Mean Temperature	.658	0.002779	0.660779
Antimalarial Treatment	-.189	-0.0004759	-0.18947
Mosquito Net Access	.074	2.5214437	2.59544
Total Population	-.180	-0.0001927	-0.18019
Total Health Centers	0	1.0956237	1.0956237



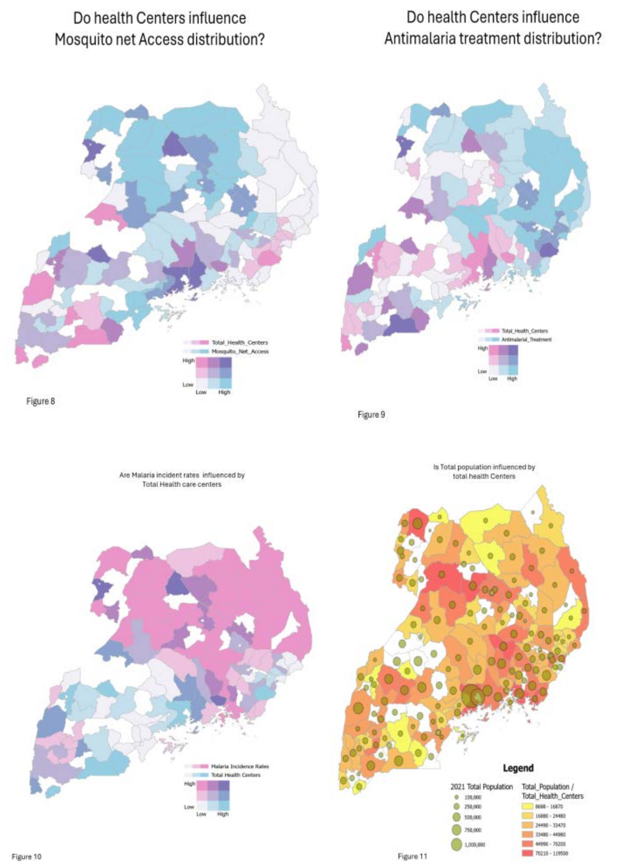
Number of health facilities, Malaria cases had no direct effect on number of health facilities.



The decomposition table provides valuable insights into the effects of different variables on malaria incidence rates. While some factors like mean temperature and mosquito net access have strong direct and indirect effects, others such as antimalarial treatment and total population primarily influence malaria incidence rates through direct effects. The total number of health centers, although having no direct effect, plays a crucial role through indirect pathways.

Bivariate color maps

bivariate color maps were used to visually assess the relationships between key pairs of variables. This technique involves combining two color gradients to create a single map where each color represents a unique combination of two variables. By using bivariate color maps, we examined the spatial relationships between Total Population and several other variables: Antimalarial Treatment, Mosquito Net Access, Mean Temperature, Total Health Centers, and Malaria Incidence Rates. Each map visually displayed the interaction between these pairs, allowing us to identify regions where high or low values of one variable coincided with high or low values of the other.



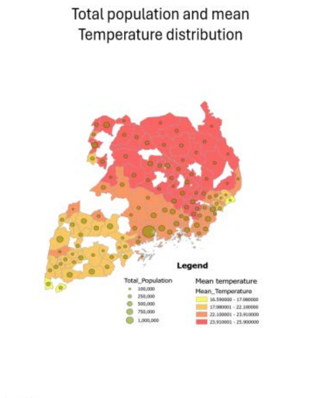


Figure 12

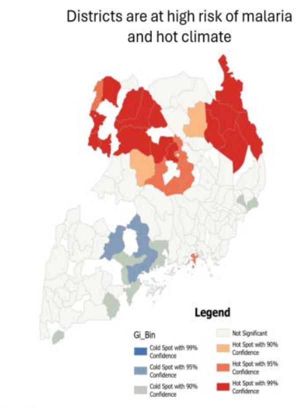


Figure 13

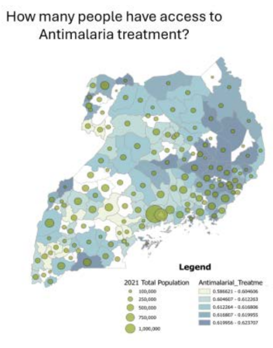


Figure 14

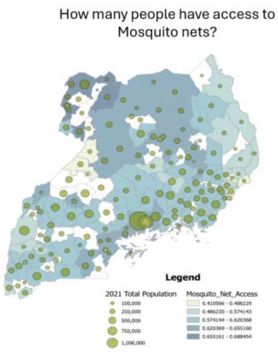


Figure 15

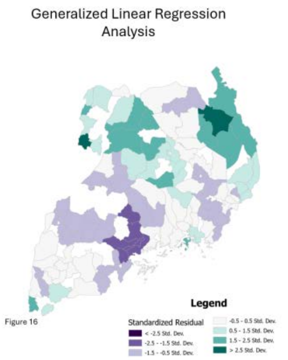


Figure 16

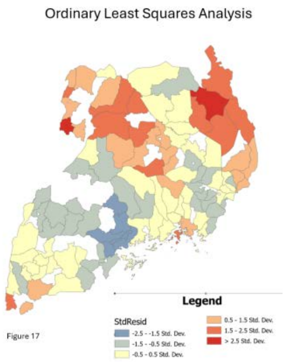


Figure 17

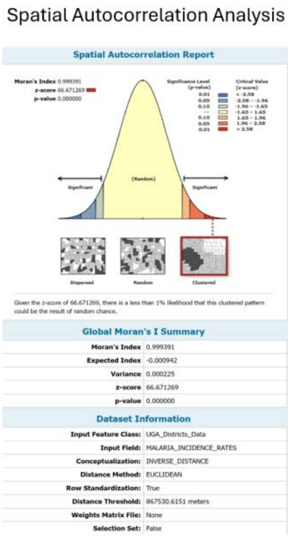


Figure 18

Statistical methods, generalized linear regression (GLR), ordinary least squares (OLS) regression and spatial autocorrelation (Moran's I)

Generalized Linear Regression (GLR) Analysis

The GLR analysis, as depicted in Figure 16, indicates that mean temperature, antimalarial treatment, mosquito net access, total population, and total health centers significantly influence malaria incidence rates, with a moderate model fit (Adjusted R^2 = 0.443). This model accounts for spatial non-stationarity and heteroskedasticity, providing a more nuanced understanding of how these factors impact malaria incidence across different regions.

Ordinary Least Squares (OLS) Analysis

The OLS regression analysis, shown in Figure 17, similarly identifies mean temperature, antimalarial treatment, mosquito net access, total population, and total health centers as significant predictors of malaria incidence rates, with a comparable model fit (Adjusted R^2 = 0.443). Specifically, mean temperature and mosquito net access show a positive relationship with malaria incidence, while antimalarial treatment and total population exhibit a negative relationship. Although the model explains approximately 44.6% of the variance in malaria incidence rates, diagnostic tests reveal issues of non-stationarity or heteroskedasticity (Koenker BP Statistic, $p < 0.01$) and non-normality of residuals (Jarque-Bera Statistic, $p < 0.01$). These findings suggest variability in relationships across the study area and potential biases in predictions. Therefore, it is recommended to use robust probabilities and the Wald Statistic for evaluating predictor significance and overall model performance, and to check for spatial autocorrelation in the residuals using the Moran's I tool.

Spatial Autocorrelation Analysis

The spatial autocorrelation analysis using Moran's I statistic for malaria incidence rates in the uga_districts_data reveals a Moran's Index of 0.999391, indicating a very strong positive spatial autocorrelation, as seen in Figure 18. This suggests that districts with similar malaria incidence rates are highly clustered together. The z-score of 66.671269, which far exceeds the critical value for statistical significance, and a p-value of 0.000000 confirm that this clustering is highly significant and unlikely to have occurred by random chance. The analysis used an inverse distance method with Euclidean distances, and row standardization was applied. These results highlight significant spatial clustering of malaria incidence rates across the study area, necessitating focused spatial interventions to address high-incidence clusters effectively.

Bivariate color maps

The maps in Figure 8 and Figure 9 highlight the critical influence of health centers on the distribution of mosquito net access and antimalarial treatment across Uganda. The data demonstrates a positive correlation between the density of health centers and the distribution of these essential health services. Regions with a higher number of health centers exhibit significantly better access to mosquito nets and antimalarial treatments, as depicted by the darker shades on the maps. This suggests that enhancing healthcare infrastructure, particularly in areas with lower health center density, could greatly improve the distribution and accessibility of malaria prevention and treatment resources. Consequently, policymakers should prioritize the expansion and strengthening of health centers in underserved regions to ensure equitable healthcare access and effective malaria control.

The maps in Figure 10 and Figure 11 highlight the critical role of health centers in influencing malaria incidence rates and population distribution across Uganda. Figure 10 shows a relationship where regions with higher densities of health centers display varied malaria incidence rates, suggesting that while some areas benefit from effective healthcare delivery, others may be influenced by additional factors such as environmental conditions. Figure 11 reveals that regions with higher population densities generally have more health centers, indicating a response to increased healthcare demands. This alignment underscores the importance of health centers in supporting large populations, but also highlights potential gaps in less populated areas. These findings suggest that while enhancing healthcare infrastructure in high-incidence regions is essential, tailored strategies addressing local health challenges and expanding health center networks in underserved areas are crucial for improving overall healthcare access and outcomes in Uganda.

The maps in Figure 12 and Figure 13 offer valuable insights into the spatial relationships between population density, mean temperature distribution, and malaria risk in Uganda. Figure 12 shows that regions with higher population densities often experience diverse temperature ranges, with northern areas generally having higher mean temperatures. This variation indicates the need for differentiated public health strategies to address heat-related illnesses and vector-borne diseases. Figure 13 identifies high-risk districts for malaria, highlighting significant hot spots in the north with high temperatures and malaria incidence. These findings suggest that targeted interventions are essential in these regions to combat malaria effectively. Public health policies should focus on improving healthcare infrastructure and implementing climate adaptation strategies to mitigate the health impacts of high temperatures and reduce malaria incidence in high-risk areas.

The maps in Figure 14 and Figure 15 highlight the disparities in access to antimalarial treatment and mosquito nets in relation to population density across Uganda. Figure 14 shows that regions with higher population densities generally have better access to antimalarial treatment, although significant gaps remain in the northern and northeastern areas. Similarly, Figure 15 reveals variations in mosquito net access, with northern regions showing relatively lower coverage despite some areas having high population densities. These disparities underscore the need for targeted public health interventions to ensure equitable access to malaria prevention and treatment resources. Enhancing healthcare infrastructure and supply chain management in underserved regions is critical to bridging the accessibility gap and improving malaria control outcomes across Uganda.

Path analysis

The decomposition analysis presented in Table 13 reveals the intricate relationships between various factors and malaria incidence rates. Mean temperature exhibits a significant direct effect ($\beta = 0.658$) and a notable indirect effect ($\beta = 0.002779$), culminating in a total effect of 0.660779. Antimalarial treatment has a strong negative direct effect ($\beta = -0.189$) with a negligible indirect effect, resulting in a total effect of -0.18947. Mosquito net access shows a considerable direct effect ($\beta = 0.074$) and a substantial indirect effect ($\beta = 2.5214437$), leading to a total effect of 2.59544. Total population presents a small direct effect ($\beta = -0.180$) and a minimal indirect effect ($\beta = -0.0001927$), yielding a total effect of -0.18019. Lastly, total health centers have no direct effect but a significant indirect effect ($\beta = 1.0956237$), resulting in a total effect of 1.0956237. These findings highlight the significant roles of mean temperature and antimalarial treatment, and the indirect influence of healthcare infrastructure and population dynamics, underscoring the complexity of factors affecting malaria incidence rates

4. Conclusion and Recommendations

Based on the decomposition analysis and statistical findings, several key recommendations can be made to effectively reduce malaria incidence rates. Enhancing mosquito net access is paramount due to its substantial total effect ($\beta = 2.59544$) on reducing malaria incidence rates. This can be achieved through widespread distribution and ensuring proper usage via community education initiatives. Maintaining and improving antimalarial treatment programs, despite their negative direct effect ($\beta = -0.189$), is essential to combat drug resistance and enhance accessibility. Furthermore, investing in healthcare infrastructure is essential, and integrating Artificial Intelligence for diagnosis would play a pivotal role. The significant indirect effect of total health centers ($\beta = 1.0956237$) highlights their role in indirectly reducing malaria incidence. Engaging local communities in environmental management strategies, such as planting trees to mitigate temperature effects and identifying mosquito breeding sites, will address the influence of mean temperature ($\beta = 0.660779$). Additionally, considering population dynamics in urban planning and health initiatives will ensure effective resource allocation. Lastly, targeted interventions in high-risk regions, particularly in the northern areas, should focus on enhancing healthcare infrastructure, improving antimalarial access, and implementing climate adaptation strategies to significantly reduce malaria incidence rates.

Future studies should investigate the scalability and adaptability of geospatial and path analysis techniques in other low-income nations with similar healthcare challenges, the long-term impacts of climate change on malaria transmission, the effectiveness of community-based interventions, and the role of socioeconomic factors. Evaluating the role of community engagement and education in enhancing the implementation of malaria control strategies and human behavior control. By addressing these factors comprehensively, policymakers and health professionals can implement more effective and sustainable malaria control and prevention measures. Specific areas for further research include assessing the scalability and adaptability of geospatial and path analysis techniques in other low-income nations with similar healthcare challenges, conducting longitudinal studies to monitor the effectiveness of expanded health center networks and targeted interventions over time, evaluating the role of community engagement and education in enhancing the implementation of malaria control strategies, and developing predictive models incorporating climate variables to better forecast malaria outbreaks and guide proactive public health responses.

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