

Modelling the Influence of Temperature on Malaria Incidence in Abuja, Nigeria: Short- and Long-Term Effects of Temperature

Olufemi Adekanmbi S.¹; Oludele J. Ayoola^{2*};
Abulwasiu Abubakar³; Victor Abah A.⁴

^{1,2,3,4}Department of Geography and Environmental Management, Centre for Sustainable Development
University of Abuja, Nigeria

Corresponding Author: Oludele J. Ayoola^{2*}

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Abstract: Malaria remains an important public health concern, and climatic conditions are recognized as important environmental determinants of malaria transmission. Temperature can influence mosquito survival, parasite development and vectorial capacity; however, the relationship between temperature and malaria incidence may vary spatially and temporally. This study assessed the relationship between mean temperature and malaria incidence across selected Area Councils of the Federal Capital Territory, Nigeria. Data covering the period 2020–2022 were examined to determine temporal and spatial patterns of malaria occurrence. Longer-term malaria incidence data were also examined using annual malaria incidence estimates and population projections. Climatic variables, particularly temperature was considered in assessing variations in malaria incidence. Malaria incidence was expressed in relation to population size to facilitate comparison among the Area Councils. The findings generally showed an inverse relationship between mean temperature and malaria incidence. Correlation coefficients varied from weak to strong negative associations across the different analyses, indicating that higher mean temperatures were generally associated with lower malaria incidence. Regression coefficients were also predominantly negative, with values ranging from approximately -0.194 to -0.607 , indicating weak to moderate inverse relationships in the respective analyses. However, the long-term regression models for the six Area Councils demonstrated very limited explanatory power, with R^2 values ranging from approximately -4% to 1% . The corresponding ANOVA results indicated that the regression models were not statistically significant at the 5% significance level. The negative R^2 values observed for some locations indicate that the models performed worse than an intercept-only model based on the mean malaria incidence. Malaria early-warning systems should therefore incorporate local climatic and epidemiological conditions rather than applying a uniform temperature threshold across all locations. Consistent, high-quality and spatially disaggregated malaria data should be maintained at health facilities and public health institutions. Accurate records of confirmed malaria cases, diagnostic methods, population at risk and seasonal patterns would improve the reliability of future climate–malaria analyses.

Keywords: Malaria Incidence; Climatic Variables; Temperature and Climate Variability.

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I. INTRODUCTION

Malaria remains one of the most important vector-borne diseases affecting populations in tropical and subtropical regions, particularly in sub-Saharan Africa. Despite substantial progress in malaria prevention, diagnosis, treatment and vector control, the disease continues to impose a considerable public health burden. The World Health Organization (WHO, 2025) estimated that approximately 282 million malaria cases and 610,000 malaria deaths occurred globally in 2024, with the WHO African Region accounting

for approximately 94% of global malaria cases and 95% of malaria deaths. Nigeria remains one of the countries contributing substantially to the global malaria burden (WHO, 2025).

The persistence of malaria in Nigeria is influenced by a complex interaction of environmental, climatic, biological, socioeconomic and health-system factors. Among these determinants, meteorological conditions are particularly important because malaria transmission depends strongly on the ecology and life cycle of *Anopheles* mosquitoes and the

development of *Plasmodium* parasites. Temperature influences mosquito survival, biting frequency, development rates and the duration of the extrinsic incubation period of the malaria parasite, whereas rainfall contributes to the formation and persistence of aquatic habitats required for mosquito breeding (Paaijmans et al., 2010; Mordecai et al., 2013). Consequently, variations in temperature and rainfall can substantially influence the intensity and seasonality of malaria transmission.

The relationship between climatic variables and malaria incidence, however, is unlikely to be purely linear or instantaneous. Temperature affects malaria transmission within a relatively narrow biological range, with both low and excessively high temperatures potentially reducing mosquito survival or parasite development. Mordecai et al. (2013) demonstrated that the optimal temperature for malaria transmission is substantially lower than previously assumed, highlighting the importance of nonlinear temperature-response relationships. Similarly, rainfall can have contrasting effects depending on its amount and timing. Moderate rainfall may increase the availability of mosquito breeding sites, whereas exceptionally heavy rainfall may wash away or disrupt immature mosquito habitats (Paaijmans et al., 2007; Bødker et al., 2003). These observations suggest that models assuming a simple linear relationship between climatic variables and malaria incidence may not adequately represent the underlying transmission dynamics.

Another important characteristic of the climate–malaria relationship is the presence of temporal lags. Climatic conditions may influence malaria incidence only after a period during which several biological processes occur. For example, rainfall may create suitable breeding habitats, followed by mosquito development, parasite development within the vector, infectious mosquito biting and eventual appearance of clinical malaria cases. Temperature can similarly influence several stages of the mosquito–parasite cycle before an observable change in malaria incidence occurs (Craig et al., 1999; Parham and Michael, 2010). Consequently, the climatic conditions recorded in a particular month may be associated with malaria cases occurring several weeks or months later.

Evidence from previous studies confirms the importance of lagged climatic effects. A systematic review by Hoshen and Morse (2004) showed that environmental factors can affect malaria transmission through delayed and seasonally varying pathways. More specifically, a systematic review of *Plasmodium falciparum* seasonality found considerable variation in the lag between climatic conditions and malaria transmission across geographical settings (Caminade et al., 2014). These findings indicate that the appropriate lag structure is likely to be location-specific and should be empirically investigated rather than assumed.

The situation is particularly relevant to Abuja, Nigeria, where malaria transmission exhibits pronounced seasonal variation corresponding with changes in meteorological conditions. Abuja has a tropical climate characterized by distinct wet and dry seasons, and the seasonal availability of

rainfall and variations in temperature create conditions that can influence mosquito abundance and malaria transmission. A study of malaria occurrence in Abuja using monthly data from 2000 to 2013 found a significant positive association between rainfall and malaria incidence at a one-month lag, while temperature and relative humidity demonstrated significant associations at a four-month lag (Oguntade, Shohaimi, Nallapan, & others 2020). These findings indicate that meteorological variables may influence malaria incidence in Abuja through delayed pathways rather than exclusively through contemporaneous effects.

Although the existing Abuja study provides important evidence concerning the relationship between weather variables and malaria incidence, there remains a need to investigate the possibility of nonlinear and distributed lag effects. Conventional regression approaches may inadequately capture situations in which the risk of malaria changes nonlinearly across the range of temperature or rainfall and in which the effect of an exposure is distributed over several subsequent months. Distributed lag non-linear models (DLNMs) were developed specifically to address this type of problem by allowing nonlinear exposure-response relationships and lag-response relationships to be estimated simultaneously (Gasparrini et al., 2010). The framework has been increasingly applied to investigate the health effects of environmental exposures that vary over time.

The distinction between short- and long-term effects is also important in understanding climate-sensitive malaria transmission. Short-term effects may represent immediate or delayed responses to specific rainfall and temperature events, while longer-term associations may reflect cumulative exposure, persistent seasonal conditions and ecological processes that sustain mosquito populations. Because the malaria transmission cycle involves several interconnected biological stages, climatic exposure may have effects that extend beyond the month in which the exposure occurs (Parham and Michael, 2010; Ryan et al., 2015). Failure to account for such distributed effects may therefore result in an incomplete characterization of the relationship between weather variability and malaria incidence.

Understanding these relationships is increasingly important in the context of changing climatic conditions. Climate variability and climate change may alter the geographical and temporal suitability of environments for malaria transmission, although the direction and magnitude of these changes vary according to local ecological and climatic conditions (Gething et al., 2010; Caminade et al., 2014). Localized empirical studies are therefore essential for identifying the specific climatic conditions and lag periods associated with malaria incidence in individual settings.

Against this background, the present study seeks to model the influence of temperature and rainfall on malaria incidence in Abuja, Nigeria, with particular emphasis on nonlinear relationships and delayed effects. The study will investigate both short- and longer-term lag structures to determine how changes in temperature and rainfall are associated with subsequent variations in malaria incidence.

By applying an appropriate time-series modelling framework, such as a distributed lag non-linear model, the study aims to provide a more comprehensive understanding of climate-sensitive malaria transmission in Abuja and generate evidence that may support climate-informed malaria surveillance, early warning and control strategies.

II. MATERIALS AND METHODS

➤ Study Area

According to Dawam (2000), the Federal Capital Territory Abuja is situated between latitude $8^{\circ} 25''$ and $9^{\circ} 25''$ North of the Equator and longitude $6^{\circ} 45''$ and $7^{\circ} 45''$ East of the Greenwich Meridian. The Federal Capital Territory Abuja covers an area of 8,000 square kilometers and occupies about 0.87% of Nigeria within the region generally referred

to as the “Middle Belt” (Wikipedia retrieved 2023). Abuja is bordered on all sides by four states namely Niger, Nasarawa, Kogi and Kaduna. In 2022, the world bank estimated total population of the FCT to be about 3.65 million with a density of 703 persons per km² (World Bank, 2022). However, according to the National Bureau of Statistics, Nigeria, the estimated population of the FCT Abuja in 2023 is 3,839,646 (NBS, 2023)

The territory is bounded by significant relief features, physiologic regions, a sufficiently unique Climatic, Vegetation and hydrological systems that have made it ideal for locating Nigeria’s new Federal Capital. It is currently home to the three tiers of government as well as a local authority the Ministry of the Federal Capital and the Federal Capital Development Authority.

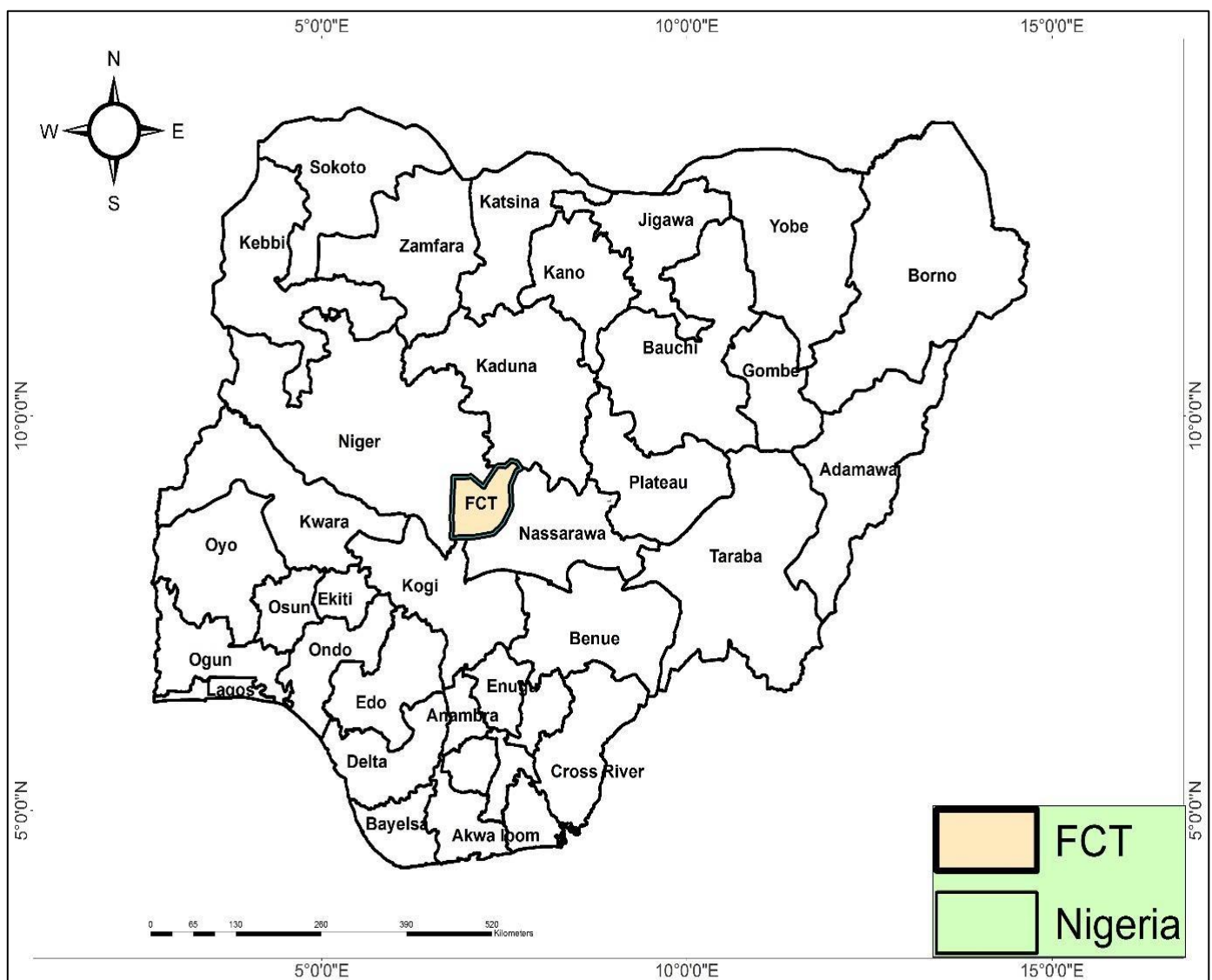


Fig 1 Map of Nigeria Showing FCT
Source: FCDA, Cartography Department.

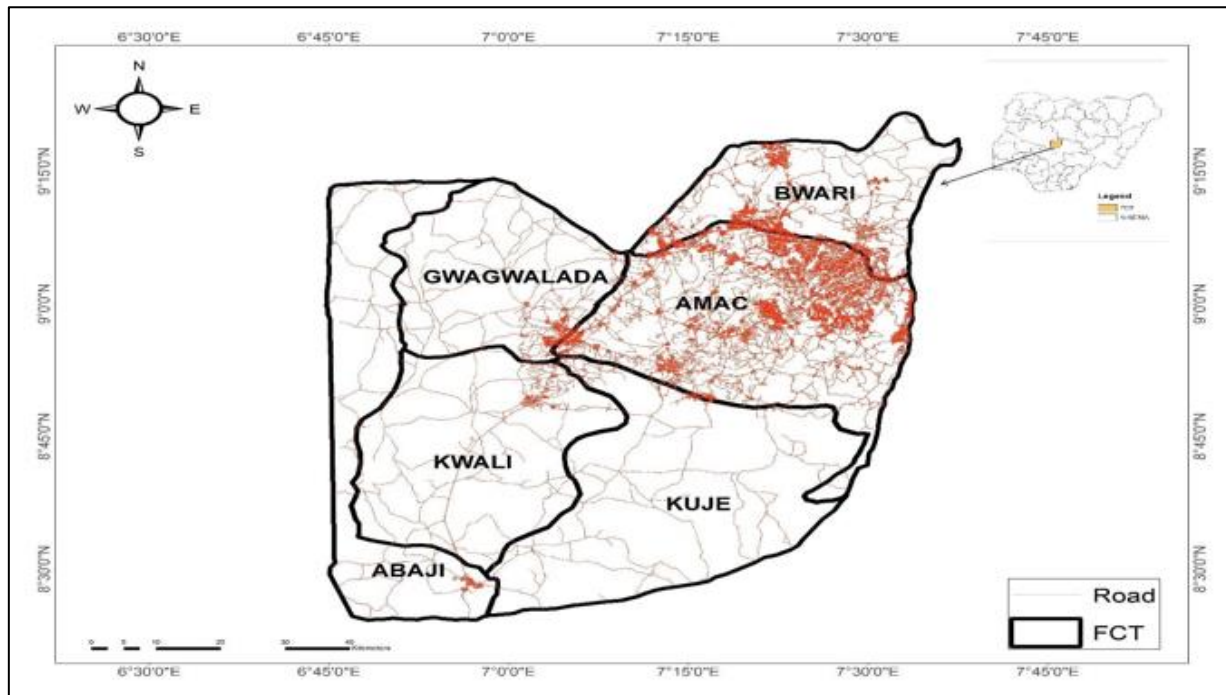


Fig 2 Study Area Map

Source: Agis, 2021.

➤ Sampling Procedure

The data used in the study was mainly secondary in nature. Data was collected from (willing) hospitals within the FCT (Table 1), the Nigerian Meteorological Agency (NIMET), the Nigerian Population Commission, and The Nigerian Bureau of Statistics. Climate data was sourced from the year 2000 to 2021 via NASA/NOAA on the website <https://power.larc.nasa.gov/data-access-viewer/>. Annual malaria incidence data was obtained from the World Bank country archives on malaria incidence.

The data collected were subjected to preprocessing to ascertain their validity and to also put them in a format suitable for analysis (Coll *et. al.*, 2020). For instance, climate data obtained from the National Oceanic and Atmospheric Administration (NOAA) was converted from its csv format to exl format suitable for analysis in Microsoft excel and SPSS statistical software Packages. The climate data was also subjected to other quality measures as recommended by Costas *et. al.*, (2021) including but not limited to A students T-test to ascertain the suitability of the data for regression analysis.

Table 1 Selected Health Centers in the Study Area

S/N	Area Council	Selected Health Centres
1	AMAC	National Hospital
2	Gwagwalada	University of Abuja Teaching hospital
3	Bwari	Bwari General Hospital
4	Kwali	Kwali General Hospital
5	Kuje	Kuje General Hospital
6	Abaji	Abaji General Hospital

Source: Reconnaissance/field survey 2023

The analysis was driven by the duration of the climate data available, specifically annual incidence and monthly incidences. Monthly averages for rainfall and temperature obtained from NIMET (2021 to 2022) and Annual climate data from NOAA (2000 to 2018) to be precise.

Establishing the relationship between malaria incidence and climatic indices was done by calculating the correlation coefficient of the data sets.

$$Correl(X, Y) = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}} \quad eq1$$

Where X is independent variable

Y is the dependent variable (Malaria incidence)

Regression analysis

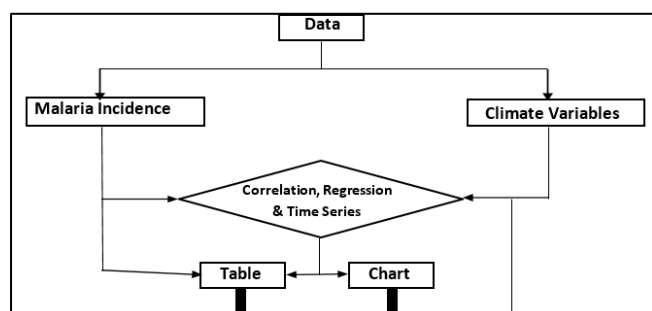


Fig 3 Flowchart Showing the Research Method. (Study.com, 2023).

$$b = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sum (x - \bar{x})^2} \quad \text{eq2}$$

Where X is independent variable

Y is the dependent variable (Malaria incidence)

Multiplicative time series trend analysis model was used for predicting future malaria incidence based on available monthly climatic data while regression analysis was used to ascertain annual data. All analysis are carried out using the Microsoft Statistical Package (EXCEL) and IBM's Statistical Package for Social Sciences (SPSS).

III. RESULTS AND DISCUSSIONS

➤ Monthly Correlation between Malaria and Temperature in Federal Capital Territory between 2020 to 2022

• Correlation between Malaria and Mean Temperature in Amac

The correlation analysis between malaria incidence and mean temperature in 2020 produced a Pearson correlation coefficient of -0.771 (Fig. 1). This indicates a strong negative correlation between the two variables. Thus, higher mean temperatures were associated with lower malaria incidence during the period examined.

Similarly, the correlation analysis for 2021 yielded a Pearson correlation coefficient of -0.745 between mean temperature and malaria incidence (Fig. 2). This also indicates a strong negative correlation, suggesting that malaria incidence tended to decrease as mean temperature increased.

For the third analysis, the correlation coefficient between mean temperature and malaria incidence was -0.345 (Fig. 3). This represents a weak negative correlation, indicating a slight tendency for malaria incidence to decrease as mean temperature increased.

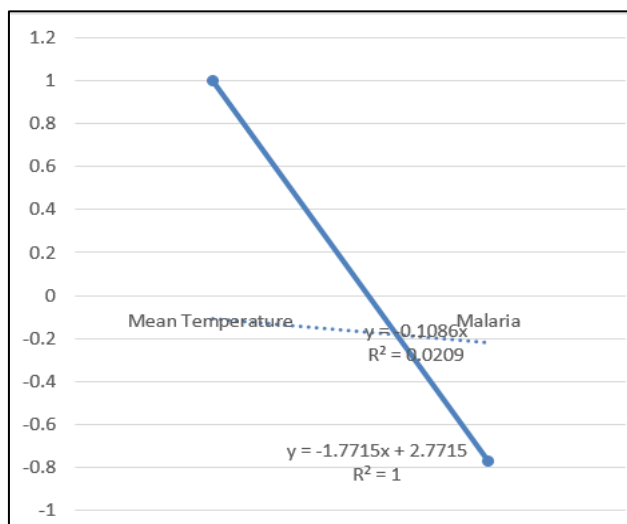


Fig 1 Correlation Coefficient (Malaria and Mean T, 2020)

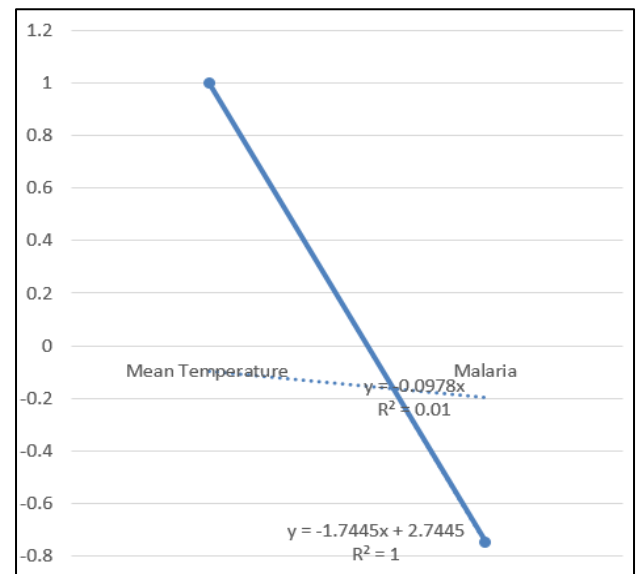


Fig 2 Correlation Coefficient for Malaria and Mean T in 2021

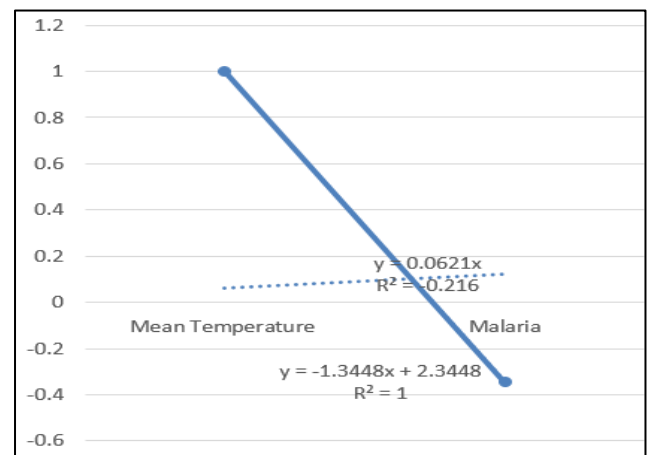


Fig 3 Correlation Coefficient of Malaria and Mean T for AMAC in 2022.

• Correlation between Malaria and Mean Temperature in Bwari

The correlation analysis revealed a coefficient of -0.702 between mean temperature and malaria incidence shown in Fig. 4, indicates a strong negative correlation between the two variables, suggesting that higher mean temperatures were associated with lower malaria incidence. However, correlation alone does not establish a causal relationship, and the observed association may not be sufficient to reliably predict malaria incidence based on mean temperature alone.

In 2021, the correlation coefficient between mean temperature and malaria incidence was -0.361 (Fig. 5), indicating a moderate negative correlation between the two variables. This suggests that malaria incidence tended to decrease as mean temperature increased. However, the relatively moderate strength of the relationship indicates that mean temperature alone may not adequately explain variations in malaria incidence.

Similarly, in 2022, the correlation coefficient between mean temperature and malaria incidence was -0.409 (Fig. 6), indicating a moderate negative correlation. This finding suggests that increases in mean temperature were associated with decreases in malaria incidence. As with the preceding years, however, the strength of the correlation does not imply that changes in mean temperature alone were sufficient to produce significant changes in malaria incidence.

Overall, the results indicate that the climatic variables examined had negative associations with malaria incidence during the study period. Although these relationships suggest that increases in mean temperature were generally associated with reductions in malaria incidence, the correlations were not sufficiently strong to establish that changes in mean temperature alone were responsible for variations in malaria incidence. Other environmental, demographic, epidemiological, and socioeconomic factors may also have contributed to the observed patterns.

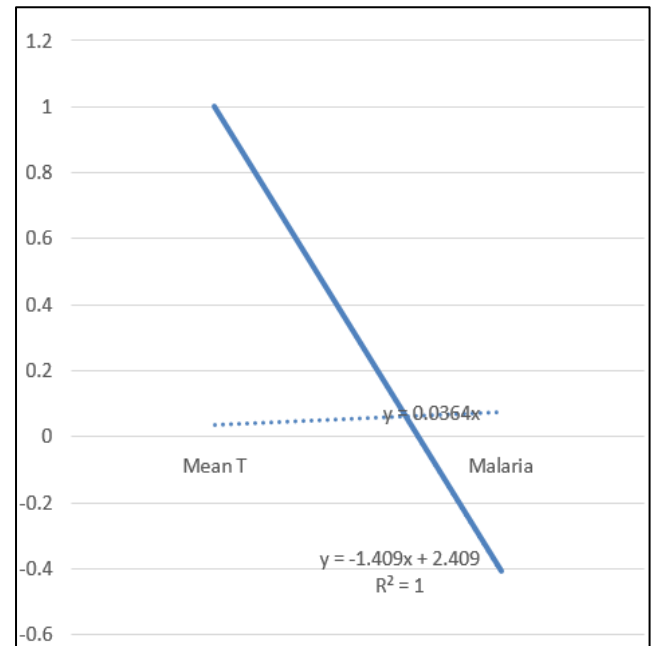


Fig 6 Correlation Coefficient for Malaria and Rainfall in Bwari for 2022

- *Correlation between Malaria and Mean Temperature in Kuje*

The correlation analysis revealed a coefficient of -0.744 between mean temperature and malaria incidence (Fig. 7), indicating a strong negative correlation between the two variables. This suggests that higher mean temperatures were associated with lower malaria incidence. However, correlation does not necessarily imply causation, as malaria incidence may also be influenced by other climatic and environmental factors, including rainfall, humidity, altitude, and other epidemiological factors.

Similarly, the correlation coefficient between mean temperature and malaria incidence was -0.720 (Fig. 8), indicating another strong negative correlation. The result suggests that malaria incidence tended to decrease as mean temperature increased. Nevertheless, the observed relationship should be interpreted cautiously, as changes in malaria incidence may be influenced by multiple interacting factors beyond mean temperature.

In contrast, the correlation coefficient between mean temperature and malaria incidence was -0.393 (Fig. 9), indicating a moderate negative correlation. This suggests that increases in mean temperature were associated with decreases in malaria incidence, although the relationship was weaker than those observed in Figures 7 and 8. The finding further indicates that mean temperature alone may not sufficiently explain variations in malaria incidence.

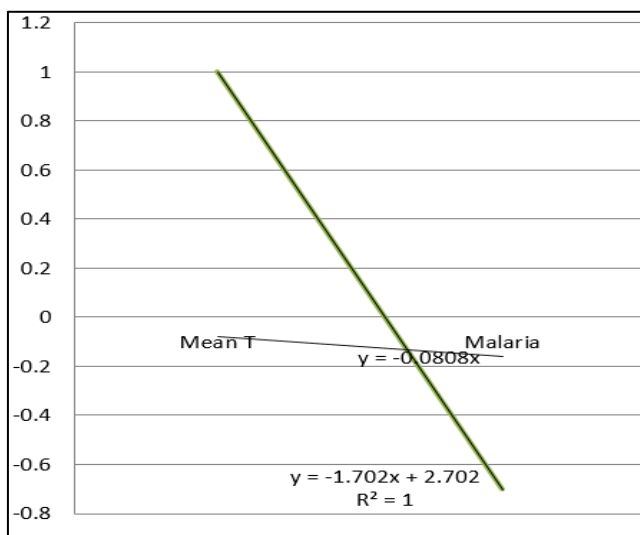


Fig 4 Correlation Coefficient for Malaria and Mean T in Bwari for 2020

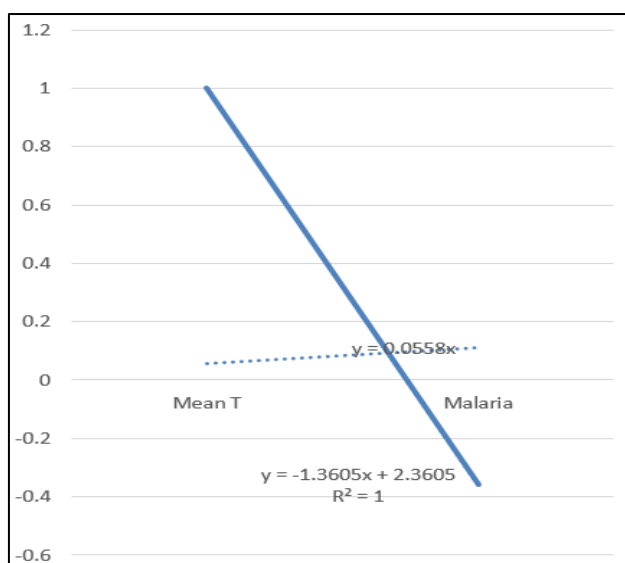


Fig 5 Correlation Coefficient for Malaria and Mean T for 2021

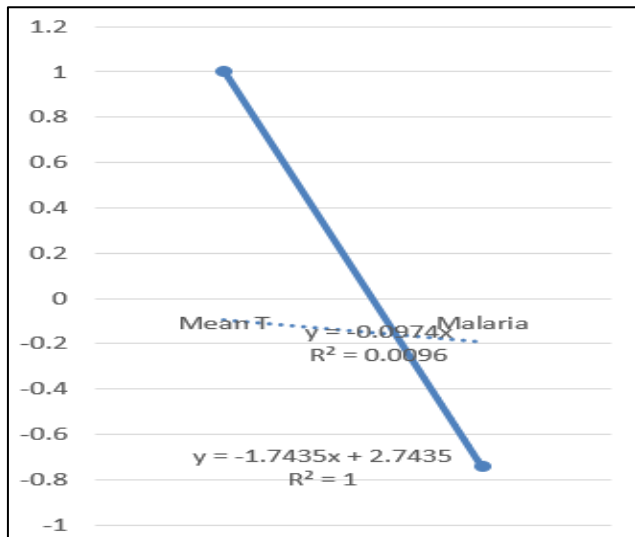


Fig 7 Correlation Coefficient for Malaria and Mean Temperature in Kuje for 2020

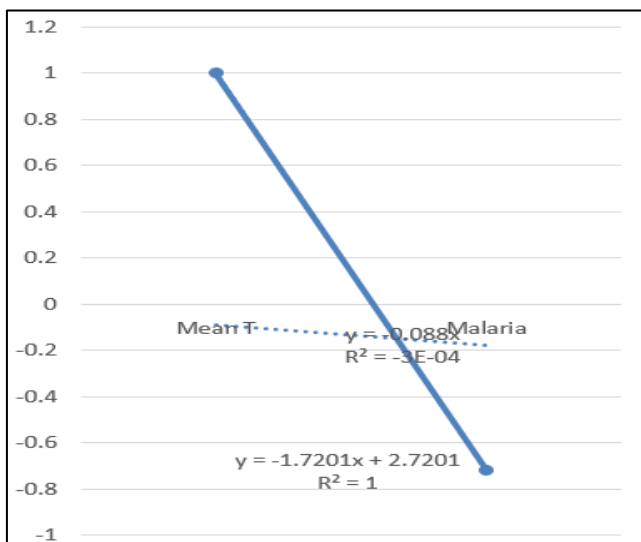


Fig 8 Correlation Coefficient for Malaria and Mean Temperature in Kuje for 2021

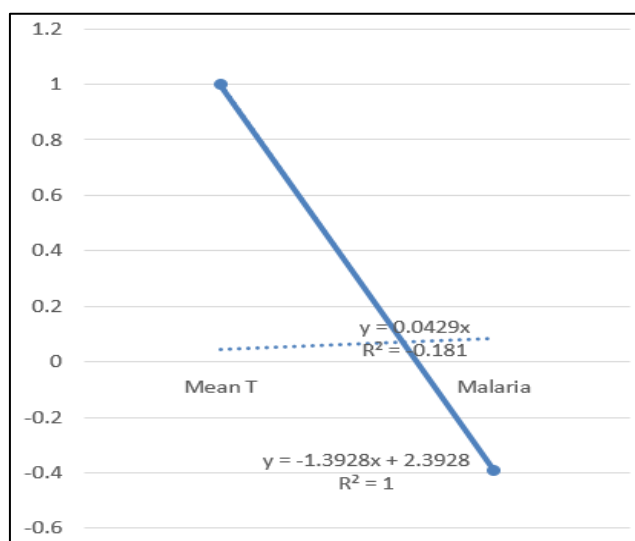


Fig 9 Correlation Coefficient for Malaria and Mean Temperature in Kuje for 2022

- *Correlation between Malaria and Mean Temperature in Gwagwalada*

The correlation analysis between mean temperature and malaria incidence yielded a coefficient of -0.647 (Fig. 10), indicating a strong negative correlation between the two variables. This suggests that higher mean temperatures were associated with lower malaria incidence. However, it is important to note that correlation does not imply causation, and other climatic, environmental, and epidemiological factors may also influence malaria incidence.

In 2021, the correlation coefficient between mean temperature and malaria incidence was -0.662 (Fig. 11), indicating a strong negative correlation. The result suggests that increases in mean temperature were associated with decreases in malaria incidence. Nevertheless, this relationship should not be interpreted as evidence that changes in temperature alone caused variations in malaria incidence.

In 2022, the correlation coefficient between mean temperature and malaria incidence was -0.356 (Fig. 12), indicating a weak negative correlation between the two variables. This finding suggests a slight tendency for malaria incidence to decrease as mean temperature increased. The weaker correlation compared with the previous year's indicates that mean temperature had a less pronounced association with malaria incidence in 2022.

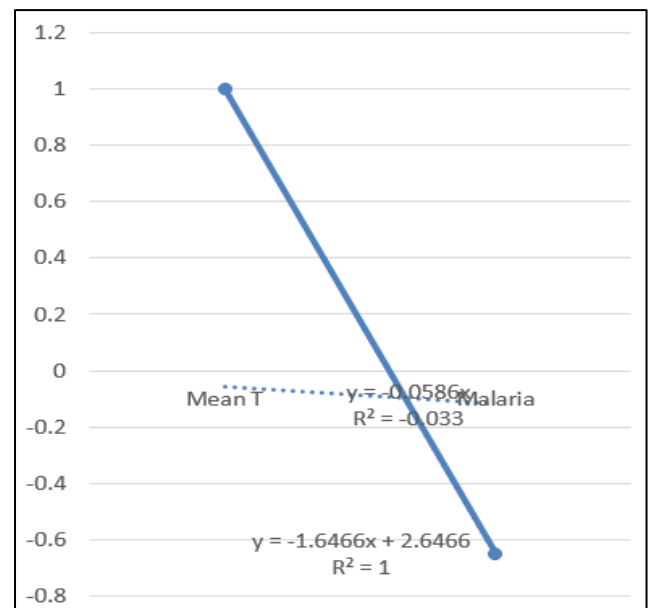


Fig 10 Correlation Coefficient for Malaria and Mean Temperature in Gwagwalada for 2020,

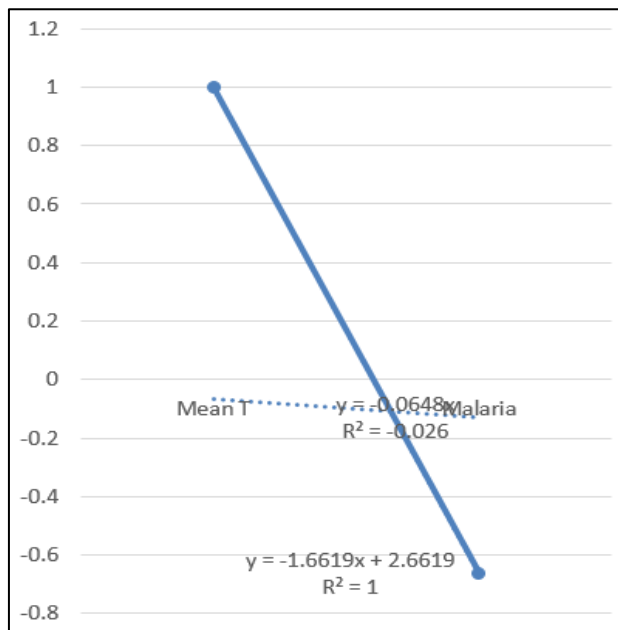


Fig 11 Correlation Coefficient for Malaria and Mean Temperature in Gwagwalada for 2021

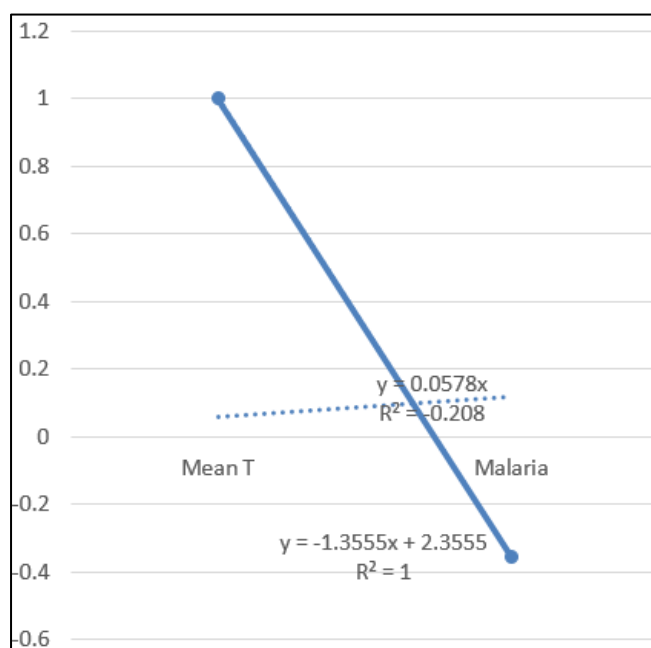


Figure 12 Correlation Coefficient for Malaria and Mean Temperature in Gwagwalada for 2022

- *Correlation between Malaria and Mean Temperature in Abaji*

The regression coefficient between mean temperature and malaria incidence was -0.430 (Fig. 13), indicating a moderate negative relationship between the two variables. This suggests that increases in mean temperature were associated with decreases in malaria incidence. However, the magnitude of the coefficient indicates that the relationship was not particularly strong, suggesting that mean temperature alone may not adequately explain variations in malaria incidence.

The regression coefficient between mean temperature and malaria incidence was -0.242 (Fig. 14), indicating a weak negative relationship between the two variables. The result suggests that malaria incidence tended to decrease as mean temperature increased, although the relatively small coefficient indicates a limited association between the variables.

Similarly, the regression coefficient between mean temperature and malaria incidence was -0.194 (Fig. 15), also indicating a weak negative relationship. This finding suggests a slight tendency for malaria incidence to decrease as mean temperature increased. The relatively low coefficient further indicates that the relationship between mean temperature and malaria incidence was weak and that other factors may have contributed to variations in malaria incidence.

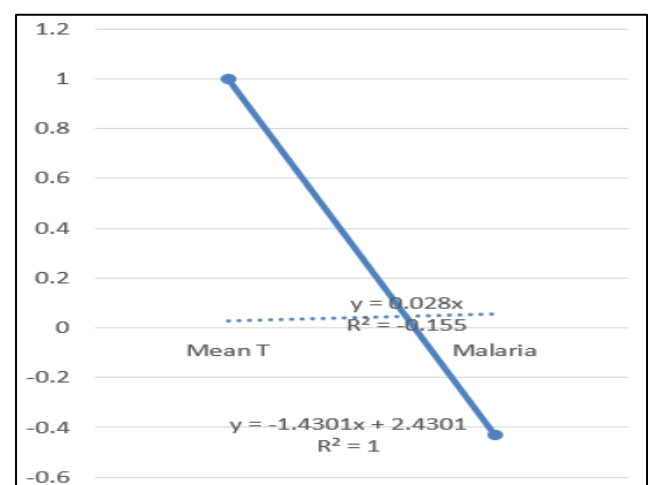


Fig 13 Correlation Coefficient for Malaria and Mean Temperature in Abaji 2020

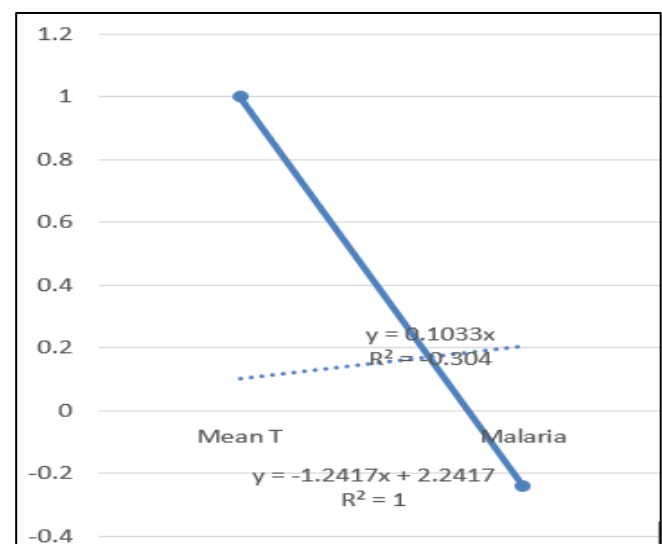


Fig 14 Correlation Coefficient for Malaria and Mean Temperature in Abaji for 2021

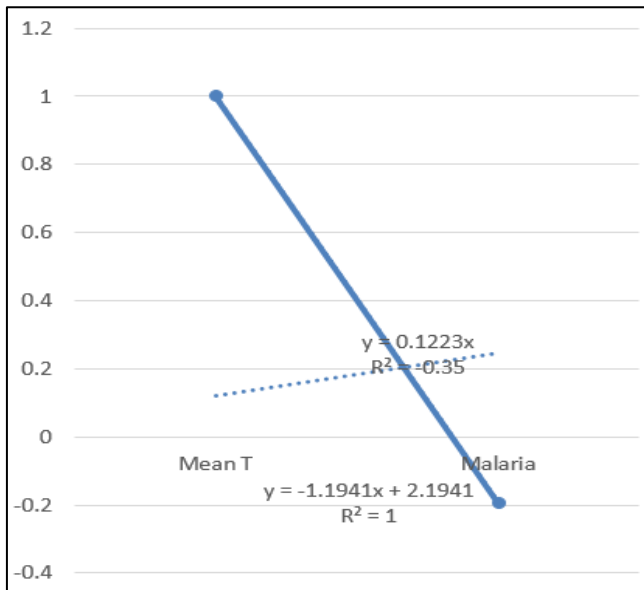


Fig 15 Correlation Coefficient for Malaria and Mean Temperature in Abaji 2022

- *Correlation between Malaria and Mean Temperature in Kwali*

The regression coefficient between mean temperature and malaria incidence was -0.544 (Fig. 16), indicating a moderate negative relationship between the two variables. This suggests that increases in mean temperature were associated with decreases in malaria incidence. However, the magnitude of the coefficient indicates that the relationship was not particularly strong, implying that mean temperature alone may not sufficiently account for variations in malaria incidence.

Similarly, the regression coefficient between mean temperature and malaria incidence was -0.607 (Fig. 17), indicating a moderate negative relationship. The result suggests that malaria incidence tended to decrease as mean temperature increased. Nevertheless, the strength of the relationship indicates that other factors may also have contributed to the observed variations in malaria incidence.

The regression coefficient between mean temperature and malaria incidence was -0.395 (Fig. 18), indicating a moderate negative relationship between the two variables. This finding suggests that increases in mean temperature were associated with decreases in malaria incidence, although the relationship was relatively weaker than those observed in Figures 16 and 17. Therefore, mean temperature alone may not adequately explain changes in malaria incidence.

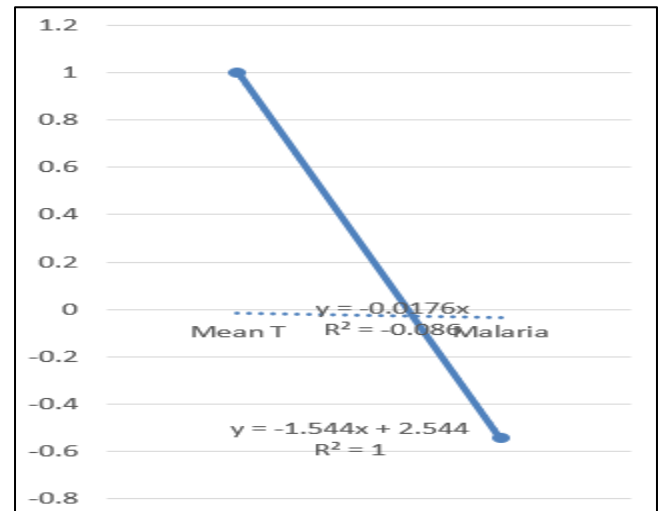


Fig 16 Correlation Coefficient for Malaria and Mean Temperature in Kwali 2020

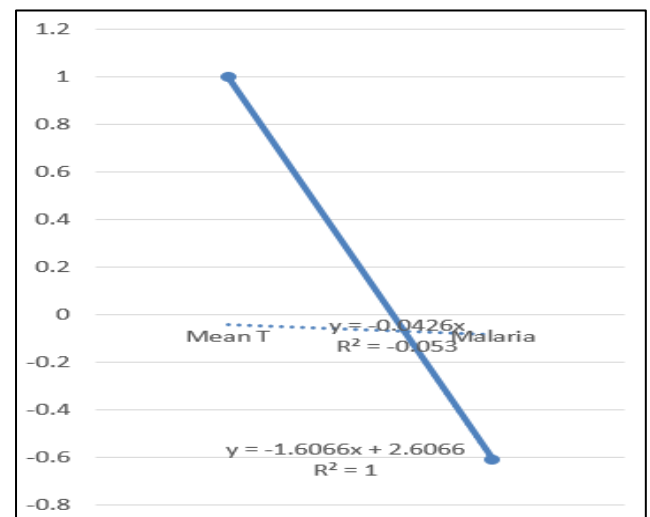


Fig 17 Regression Model (R^2) values for Malaria and Mean Temperature in Kwali for 2021

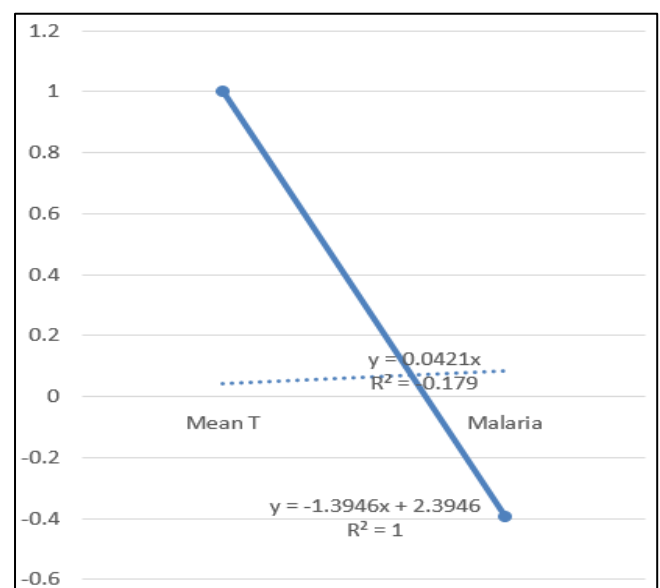


Fig 18 Regression Model (R^2) values for Malaria and Mean Temperature in Kwali for 2022

➤ Total Annual Malaria Incidence and Temperature

The regression analysis for Kuje malaria incidence (2000–2021) produced an R^2 value of approximately 1% (Fig. 19). This indicates that the explanatory variable accounted for only about 1% of the variation in malaria incidence over the study period, suggesting a very weak explanatory relationship. Furthermore, based on the p-value of the F-statistic obtained from the ANOVA table and the adopted 5% significance level, the regression model was not statistically significant. Thus, the explanatory variable did not provide substantially more information about malaria incidence than would be obtained by using the mean malaria incidence as a baseline predictor.

For Kwali malaria incidence (2000–2021), the regression model produced an R^2 value of approximately -4% (Fig. 20). The negative R^2 indicates that the model performed worse than a simple model based on the mean of the dependent variable. This suggests that the explanatory variable provided little or no useful explanatory information regarding variations in malaria incidence during the study period. In addition, the p-value of the F-statistic was not significant at the 5% level, indicating that the overall regression model did not provide a statistically significant explanation of malaria incidence.

Similarly, the regression analysis for Abaji malaria incidence (2000–2021) yielded an R^2 value of approximately -3% (Fig. 21). The negative R^2 suggests that the model did not explain the observed variation in malaria incidence better than a mean-based model. The F-test was also not statistically significant at the 5% significance level, indicating that the explanatory variable did not make a significant contribution to explaining malaria incidence during the study period.

For AMAC malaria incidence (2000–2021), the regression analysis produced an R^2 value of approximately 1% (Fig. 22). This indicates that only a very small proportion of the variation in malaria incidence was accounted for by the explanatory variable. The corresponding F-test was not statistically significant at the 5% level, indicating that the regression model did not provide a significantly better explanation of malaria incidence than the mean-based model.

The regression analysis for Gwagwalada malaria incidence (2000–2021) yielded an R^2 value of approximately -1% (Fig. 23). The negative R^2 indicates that the fitted model performed slightly worse than a model that simply predicts the mean malaria incidence. Furthermore, the F-statistic was not significant at the 5% significance level, suggesting that the explanatory variable did not provide sufficient evidence to explain variations in malaria incidence over the study period.

Finally, the regression model for Bwari malaria incidence (2000–2021) produced an R^2 value of approximately -3% (Fig. 24). This negative value indicates that the model performed worse than the baseline mean model and therefore provided little explanatory value for malaria incidence. The F-test was also not statistically significant at the 5% significance level, indicating that the explanatory

variable did not significantly improve the explanation or prediction of malaria incidence.

Conclusively, the regression results across the six locations indicate that the explanatory variable had limited explanatory power for malaria incidence between 2000 and 2021. The very low and negative R^2 values, together with the non-significant F-tests, suggest that the models did not adequately account for variations in malaria incidence across the study areas. This may indicate that malaria incidence was influenced by other climatic, environmental, demographic, socioeconomic, and epidemiological factors that were not included in the regression models.

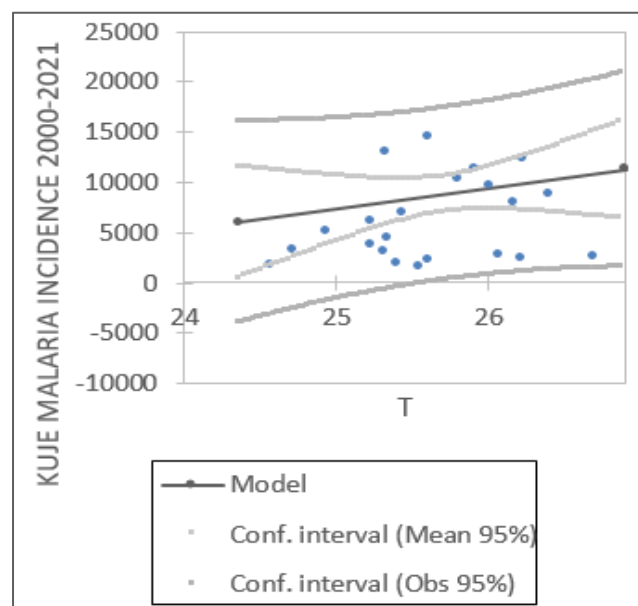


Fig 19 Regression of KUJE MALARIA INCIDENCE 2000-2021 by T ($R^2=0.058$)

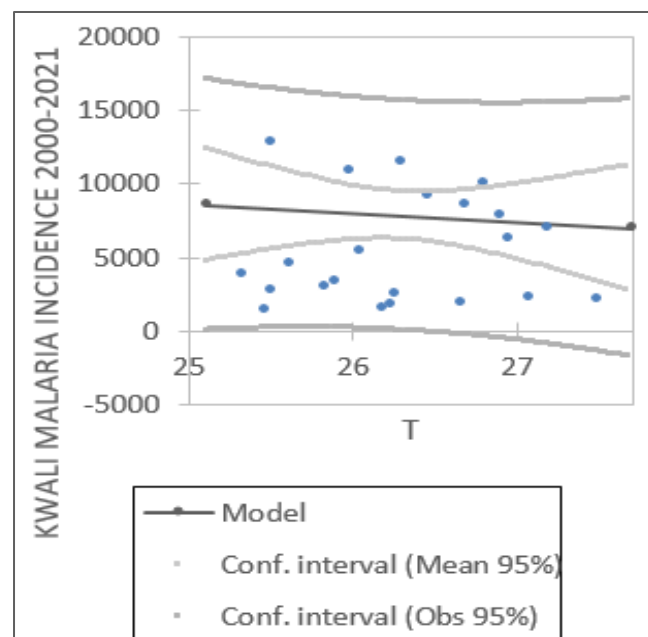


Fig 20 Regression of KWALI MALARIA INCIDENCE 2000-2021 by T ($R^2=0.010$)

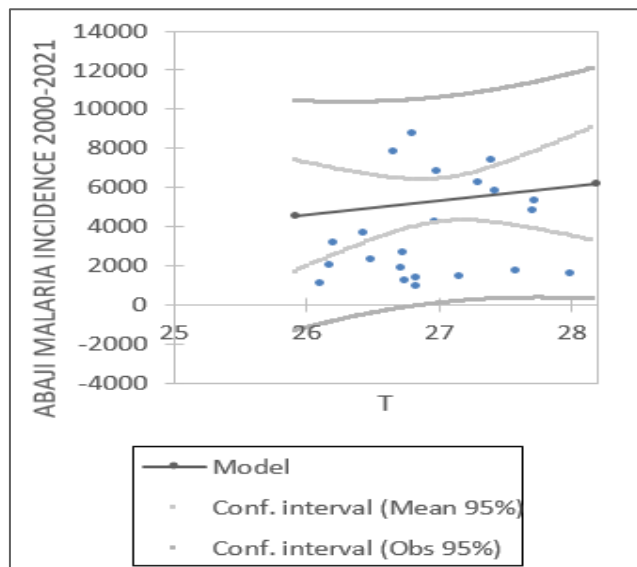


Fig 21 Regression of ABAJI MALARIA INCIDENCE 2000-2021 by T ($R^2=0.020$)

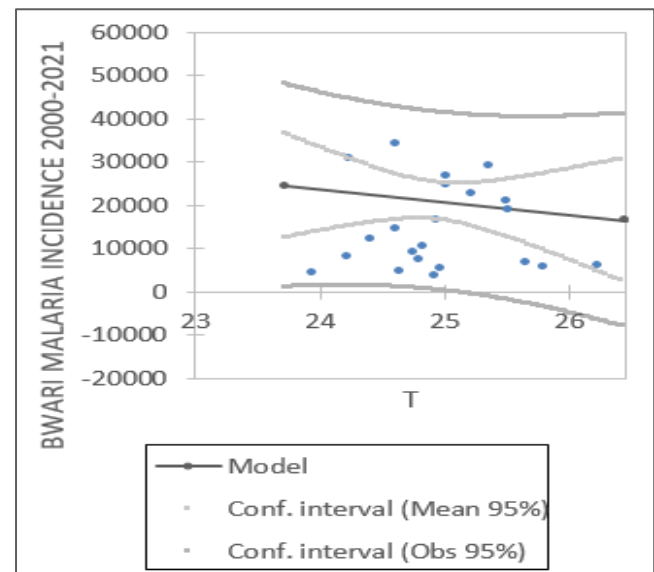


Fig 24 Regression of GWAGWALADA MALARIA INCIDENCE 2000-2021 by T ($R^2=0.037$)

IV. DISCUSSIONS OF THE RESULTS

- Discussion on the Monthly Correlation between Malaria and Temperature in Federal Capital Territory between 2020 to 2022

The regression results presented in Figures 16–18 show negative relationships between mean temperature and malaria incidence, with regression coefficients of -0.544 , -0.607 , and -0.395 , respectively. These findings indicate that increases in mean temperature were generally associated with decreases in malaria incidence, although the strength of the relationship varied among the three analyses. The negative association observed in this study is plausible because the relationship between temperature and malaria transmission is not necessarily linear. Temperature influences several components of the malaria transmission cycle, including mosquito survival, biting behaviour, parasite development and vector competence. Blanford et al. (2013) demonstrated that both mean temperature and daily temperature variation can substantially influence *Plasmodium* development within mosquitoes. Their findings further suggest that the use of mean temperature alone may either underestimate or overestimate malaria transmission potential depending on the prevailing thermal conditions.

The negative coefficients observed in the present study may therefore indicate that the temperatures experienced within the study area were approaching or exceeding conditions that are optimal for malaria transmission. Although moderate increases in temperature can enhance parasite development and mosquito activity under suitable conditions, temperatures beyond the optimal range can reduce mosquito survival and consequently reduce transmission potential. Mordecai et al. (2013) reported that malaria transmission has an optimal temperature range rather than increasing continuously with temperature. Similarly, Paaismans et al. (2012) found that warmer temperatures can reduce the vectorial capacity of malaria mosquitoes under certain thermal conditions. These findings provide a

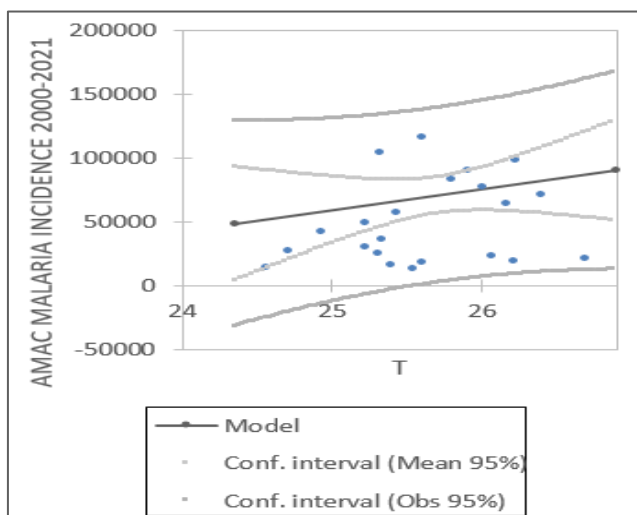


Fig 22 Regression of AMAC MALARIA INCIDENCE 2000-2021 by T ($R^2=0.058$)

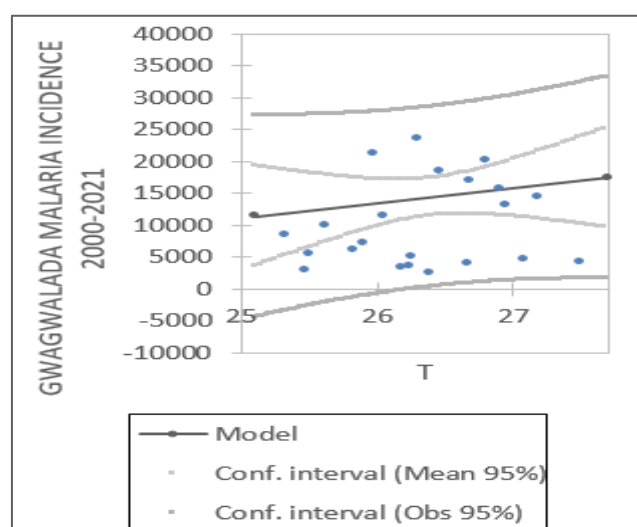


Fig 23 Regression of BWARI MALARIA INCIDENCE 2000-2021 by T ($R^2=0.022$)

biological explanation for the negative relationships observed in the present study, particularly where temperatures may have been above the optimum required for efficient malaria transmission.

The results are also comparable with the findings of Colón-González et al. (2016), who examined the effects of temperature and rainfall on malaria incidence in Rwanda and Uganda. Their study found that the effects of temperature and rainfall on malaria incidence were nonlinear and delayed, and that although climatic variables were important, other factors also contributed to variations in malaria incidence. This supports the present finding that the relationship between mean temperature and malaria incidence should not be interpreted as a simple direct relationship. The moderate negative coefficients obtained in Figures 16 and 17 (−0.544 and −0.607) suggest a relatively stronger inverse association, whereas the weaker coefficient in Figure 18 (−0.395) may indicate that other climatic or non-climatic factors exerted a greater influence on malaria incidence under the conditions represented by that analysis.

However, evidence from broader geographical studies indicates that the direction and magnitude of the temperature–malaria relationship can vary considerably between locations. Liu et al. (2024), in a worldwide observational study covering 57 countries and territories, found significant associations between temperature, precipitation and malaria incidence, but emphasized that the effects of climatic variables differed across settings. This variation may result from differences in ecological conditions, rainfall patterns, altitude, mosquito species, human behaviour, socioeconomic conditions and malaria-control measures. Consequently, the negative regression coefficients obtained in the present study may reflect the specific climatic and ecological conditions of the study area rather than a universal relationship between temperature and malaria incidence.

The findings of the present study are consistent with previous research demonstrating that temperature is an important determinant of malaria transmission but that its influence is complex, nonlinear and dependent on local environmental conditions. The negative coefficients suggest that higher mean temperatures were associated with lower malaria incidence during the study period. Nevertheless, these results should not be interpreted as evidence that increasing temperature directly causes a reduction in malaria incidence. Rather, temperature may interact with rainfall, humidity, altitude, mosquito ecology, parasite development and other epidemiological factors to influence malaria transmission. The observed relationships therefore provide evidence of an inverse association between mean temperature and malaria incidence while highlighting the need to consider multiple climatic and non-climatic determinants when explaining malaria patterns.

➤ *Discussions of the Total Annual Malaria Incidence and Temperature*

The regression analysis for the six Area Councils—Kuje, Kwali, Abaji, AMAC, Gwagwalada and Bwari—showed very low explanatory power, with R^2 values ranging

from approximately −4% to 1%. The corresponding ANOVA results were also not statistically significant at the 5% significance level, indicating that the explanatory variable, considered within these simple regression models, did not significantly improve the explanation of malaria incidence compared with a model based only on the mean. These findings suggest that malaria incidence during 2000–2021 was influenced by factors beyond the explanatory variable included in the models. This interpretation is consistent with Colón-González et al. (2016), who found that although temperature and rainfall were associated with malaria incidence in Rwanda and Uganda, climatic variables alone did not fully account for variations in malaria incidence and that other factors also played an important role. Their study further demonstrated that the effects of temperature and rainfall were nonlinear and occurred with time lags.

The very low R^2 values obtained in the present study can also be explained by the complex and nonlinear relationship between malaria transmission and climatic conditions. Malaria transmission depends on several interacting processes, including mosquito survival, vector abundance, parasite development, rainfall, humidity and temperature. Evidence from community-level studies in Africa and Asia indicates that both temperature and precipitation can have unimodal relationships with malaria, whereby malaria risk initially increases with climatic conditions but declines after certain thresholds are exceeded. This provides a possible explanation for why a simple linear regression model may perform poorly in the present study. If the relationship between the climatic variable and malaria incidence is nonlinear, a conventional linear model may fail to capture the underlying pattern, resulting in very low or even negative R^2 values.

The findings are also comparable with research conducted specifically in Abuja, Nigeria. A weather–malaria modelling study using data from 2000–2013 found that rainfall, temperature and relative humidity significantly influenced malaria incidence, but the effects differed according to the time lag considered. Rainfall had a significant effect at a one-month lag, while temperature and humidity also showed significant effects at longer lags. The authors concluded that the relationship between malaria and weather variables was affected by seasonality and lagged climatic effects. This is particularly relevant to the present findings because the analysis for the six Area Councils appears to have relied on a relatively simple explanatory structure. If temperature or rainfall affects malaria incidence several weeks or months later, a contemporaneous linear regression may fail to capture that relationship and consequently produce a very low R^2 and a non-significant F-test.

Similarly, Adepoju et al. in their spatio-temporal analysis of malaria in Nigeria demonstrated that the association between malaria incidence and environmental variables varied according to the statistical model and spatial structure. Their analysis found significant relationships involving rainfall, temperature, aridity and proximity to water, but the direction and magnitude of these associations

differed between ordinary least squares, spatial lag and spatial error models. This supports the possibility that the weak explanatory power observed in Kuje, Kwali, Abaji, AMAC, Gwagwalada and Bwari may partly reflect the limitations of applying a simple regression model to a disease that has substantial spatial and temporal variability.

Further evidence comes from a study in Ondo State, Nigeria, where multiple linear regression showed that average maximum temperature made a statistically significant contribution to explaining malaria incidence, with a standardized regression coefficient of -0.605 , while rainfall and relative humidity made smaller contributions in that particular model. This result differs from the present finding of non-significant overall models, but the difference is informative. It suggests that the importance of individual climatic variables can vary considerably according to geographical location, period of observation, model specification and the combination of variables included. Therefore, the absence of a significant overall relationship in the present analysis does not necessarily mean that climate has no influence on malaria transmission; rather, it may indicate that the particular explanatory variable and model specification used did not adequately capture the mechanisms driving malaria incidence in the six Area Councils.

The negative R^2 values observed for Kwali (-4%), Abaji (-3%), Gwagwalada (-1%) and Bwari (-3%) require particular attention. A negative R^2 in this context should not be interpreted as meaning that the explanatory variable “explained -4% , -3% , or -1% of malaria incidence.” Instead, it indicates that the fitted regression model performed worse than the intercept-only model that predicts the mean malaria incidence. Thus, these results provide evidence that the simple regression specification had little predictive or explanatory value for those Area Councils. The approximately 1% R^2 obtained for Kuje and AMAC similarly indicates that only a very small proportion of the variation in malaria incidence was captured by the explanatory variable.

The weak model performance may also reflect the fact that malaria incidence is affected by numerous non-climatic factors, including malaria-control interventions, availability and use of insecticide-treated nets, indoor residual spraying, access to healthcare, diagnostic practices, population growth, urbanization, socioeconomic conditions and changes in surveillance systems. Recent research has emphasized that malaria risk is shaped by interactions among environmental, geographical, socioeconomic and epidemiological factors rather than by a single climatic variable. In addition, a recent Nigerian study using panel data emphasized the importance of incorporating multiple climatic variables and lagged malaria cases when modelling malaria incidence, illustrating the limitations of models that attempt to explain incidence using only a small number of contemporaneous predictors.

The findings from Figures 19–24 indicate that the explanatory variable used in the present regression models did not adequately explain variations in malaria incidence across the six Area Councils between 2000 and 2021. This result is consistent with previous research showing that

malaria transmission is a complex process involving nonlinear climatic effects, time lags, spatial variation and multiple environmental and socioeconomic determinants. The low and negative R^2 values should therefore not be interpreted as evidence that climatic conditions are irrelevant to malaria transmission. Rather, they suggest that a simple regression model based on the explanatory variable alone was insufficient to capture the complexity of malaria dynamics in the study area. Future analyses could improve the explanatory power of the models by incorporating rainfall, temperature, relative humidity, lagged climatic variables, population characteristics and malaria-control interventions, as well as considering nonlinear and spatial or time-series modelling approaches.

V. CONCLUSION AND RECOMMENDATIONS

The findings generally revealed an inverse relationship between mean temperature and malaria incidence, although the strength of this association varied across years and locations. The correlation coefficients obtained in the analyses ranged from weak to strong negative relationships, indicating that higher mean temperatures were generally associated with lower malaria incidence. The strongest negative associations were observed in some of the annual analyses, while weaker relationships were recorded in others. This variation demonstrates that the relationship between temperature and malaria incidence was not consistent across all periods and locations.

The regression analyses further demonstrated that mean temperature alone had limited explanatory power for malaria incidence in several of the study areas. The regression coefficients were predominantly negative, while the R^2 values for Kuje, Kwali, Abaji, AMAC, Gwagwalada and Bwari were very low, ranging from approximately -4% to 1% . The corresponding ANOVA results indicated that the regression models were not statistically significant at the 5% significance level. The negative R^2 values observed for some Area Councils indicate that the respective models performed worse than an intercept-only model based on the mean malaria incidence. Therefore, the results do not support the use of mean temperature alone as a reliable predictor of malaria incidence over the study period.

The observed inverse relationship between temperature and malaria incidence is biologically plausible because malaria transmission is influenced by an optimum range of temperature rather than increasing continuously with increasing temperature. Temperatures above or below the optimal range can adversely affect mosquito survival, parasite development and vectorial capacity. However, malaria transmission is a complex process influenced by multiple climatic, environmental, demographic, socioeconomic and epidemiological factors. Rainfall, relative humidity, altitude, vegetation, mosquito ecology, population characteristics, healthcare access and malaria-control interventions may modify the effect of temperature on malaria transmission.

The differences observed among the Area Councils and across years further suggest that the temperature–malaria relationship is spatially and temporally heterogeneous. Consequently, the relatively weak regression performance should not be interpreted to mean that climatic conditions are unimportant to malaria transmission. Rather, it indicates that a simple linear relationship between mean temperature and malaria incidence is insufficient to explain the observed patterns. The findings support the need for integrated approaches that consider multiple climatic variables, temporal lags, nonlinear relationships and local environmental and socioeconomic conditions.

Conclusively, the study establishes that mean temperature was negatively associated with malaria incidence during the period investigated, but the strength and statistical contribution of this relationship varied considerably. The findings therefore provide evidence that temperature is an important component of the climatic context of malaria transmission, but it should not be considered an independent or sufficient predictor of malaria incidence. More comprehensive modelling incorporating multiple climatic and non-climatic determinants is required to improve understanding and prediction of malaria transmission in the study area..

➤ Recommendations

- The differences observed among Kuje, Kwali, Abaji, AMAC, Gwagwalada and Bwari demonstrate that the relationship between climate and malaria may vary spatially. Malaria early-warning systems should therefore incorporate local climatic and epidemiological conditions rather than applying a uniform temperature threshold across all locations.
- Consistent, high-quality and spatially disaggregated malaria data should be maintained at health facilities and public health institutions. Accurate records of confirmed malaria cases, diagnostic methods, population at risk and seasonal patterns would improve the reliability of future climate–malaria analyses.
- Public health surveillance should incorporate mean temperature together with rainfall, relative humidity and other relevant environmental variables. The weak explanatory power of temperature-only models indicates that malaria surveillance and prediction should not rely on a single climatic indicator.
- Since climatic conditions may influence mosquito populations and parasite development several weeks or months before changes in malaria incidence become apparent, future studies should examine lagged relationships between temperature, rainfall, humidity and malaria cases rather than relying solely on contemporaneous observations.
- Future research should consider nonlinear regression, generalized additive models, distributed lag models, time-series models and other appropriate approaches capable of capturing threshold effects and nonlinear relationships between climate and malaria incidence. The low R^2 values obtained from the linear models suggest that simple linear regression may not adequately represent the underlying transmission dynamics.
- The differences observed among Kuje, Kwali, Abaji, AMAC, Gwagwalada and Bwari demonstrate that the relationship between climate and malaria may vary spatially. Malaria early-warning systems should therefore incorporate local climatic and epidemiological conditions rather than applying a uniform temperature threshold across all locations.
- Consistent, high-quality and spatially disaggregated malaria data should be maintained at health facilities and public health institutions. Accurate records of confirmed malaria cases, diagnostic methods, population at risk and seasonal patterns would improve the reliability of future climate–malaria analyses.
- Future studies should incorporate variables such as population density, land use, altitude, socioeconomic conditions, healthcare accessibility, mosquito-control interventions, use of insecticide-treated nets and indoor residual spraying. Including these variables would provide a more comprehensive explanation of variations in malaria incidence.
- Malaria-control programmes should continue to emphasize established interventions such as insecticide-treated nets, indoor residual spraying, environmental management, prompt diagnosis and effective treatment. Climatic information should complement rather than replace these established public health measures.
- Longer-term studies using monthly or seasonal rather than annual data would help identify delayed and seasonal relationships between climatic conditions and malaria incidence. Spatial statistical and geospatial approaches could also help identify areas where climatic and environmental conditions create greater malaria transmission risk.
- Health authorities should consider routinely incorporating meteorological information into malaria preparedness and planning. However, such information should be interpreted alongside epidemiological surveillance and other relevant determinants because the present findings demonstrate that mean temperature alone has limited predictive capacity.

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