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Effect of Urban Heat Island on Meningitis: Insights from Remote Sensing Analysis

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Abstract – The interaction between urban heat islands (UHIs) and public health is an increasing concern, particularly in semi-arid regions such as Kano Metropolis. Although prior research has identified links between climatic factors and infectious diseases, the specific connection between UHI intensity and meningitis incidence remains insufficiently studied. This study utilized remote sensing methods to examine spatial and temporal UHI patterns through satellite imagery from 2015 to 2023. Epidemiological data on meningitis cases were combined with UHI maps to analyze correlations and identify high-risk zones. Statistical analyses, including ordinal logistic regression, were employed to evaluate the relationship between UHI intensity and disease prevalence. The results demonstrated a strong correlation between UHI intensity and meningitis incidence, with 73% of cases occurring in areas classified under the "Strongest" UHI category. Temporal analysis identified 2017 as the peak year, contributing 94% of the recorded cases. Regression analyses confirmed significant associations, with UHI intensity emerging as a key predictor of meningitis risk (p = 0.01). Spatial visualizations revealed clusters of cases in areas with high UHI intensity, underscoring the compounded health risks in densely urbanized regions. This study emphasizes the significant influence of UHIs on meningitis patterns in Kano Metropolis. The findings highlight the necessity of climate-responsive urban planning and focused public health strategies to reduce disease risks in rapidly urbanizing environments.

Keywords *– Urban heat island (UHI), Public health, Semi-arid region, Remote sensing, Meningitis*

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1.0 Introduction

The escalating impacts of climate change and rapid urbanization present growing public health concerns globally, particularly within urban environments of low- and middle-income countries. Among these, the Urban Heat Island (UHI) phenomenon has emerged as a critical environmental challenge, characterized by elevated temperatures in urban areas relative to surrounding rural zones due to land cover modification, impervious surface expansion, and anthropogenic heat emissions (Deng et al., 2024; Kong et al., 2021). The health implications of UHIs are well documented, with numerous studies establishing their contribution to heat-related illnesses, respiratory complications, and cardiovascular diseases, particularly in vulnerable urban populations (Elmarakby & Elkadi, 2024; Sarfo et al., 2023; Brimicombe et al., 2024).

In Sub-Saharan Africa, the convergence of rapid urban growth, limited infrastructure, and climate variability has amplified health risks, especially within the region known as the African meningitis belt (Diouf et al., 2024). This region, stretching from Senegal to Ethiopia, has historically witnessed recurrent epidemics of meningitis, predominantly caused by Neisseria meningitidis, with seasonal outbreaks strongly linked to climatic conditions such as temperature fluctuations and low humidity (Borrow et al., 2017; Hadley et al., 2024). Within Nigeria, Kano Metropolis represents a high-risk zone, combining dense urbanization, semi-arid climatic conditions, and recurring meningitis outbreaks (Mohammed et al., 2019; Aborode et al., 2024).

However, the theoretical connection between UHI effects and infectious disease dynamics remains underdeveloped, particularly regarding meningitis. While studies have highlighted the role of temperature extremes in aggravating disease burdens (Yang et al., 2024), few have systematically examined how localized urban heat patterns, driven by UHI intensity, influence disease transmission within African cities (Nwaogu et al., 2024). This knowledge gap reflects broader limitations in the integration of geospatial analysis with public health research, despite demonstrated successes of remote sensing and spatial models in predicting climate-sensitive diseases, such as dengue fever and COVID-19, in other regions (Sebastianelli et al., 2024; Cascante-Vega et al., 2023).

Moreover, recent studies underscore the relevance of urban planning, land use patterns, and bioclimatic conditions in shaping urban thermal environments and associated public health outcomes (Bursal Duramaz et al., 2023; Kassomenos & Begou, 2022a). In cities such as Bursa and Ankara, empirical evidence reveals how urban form, green space distribution, and building density significantly influence air quality, thermal comfort, and environmental health (Altan et al., 2022; Özkan et al., 2022). Despite such advances, few studies have applied these concepts to the African context, where rapid, often unplanned, urban expansion exacerbates heat retention and heightens vulnerability to climate-sensitive diseases.

In addition to these knowledge gaps, there remains a scarcity of localized, high-resolution studies exploring the combined influence of UHI intensity, land cover characteristics, and public health outcomes, particularly meningitis, in African cities. Furthermore, while remote sensing techniques have been extensively applied to monitor UHIs (Almeida et al., 2021), their integration with epidemiological data in semi-arid, data-scarce environments remains limited. Addressing this limitation is critical to informing targeted interventions, promoting climate-resilient urban development, and safeguarding public health in vulnerable settings such as Kano Metropolis. Urban Heat Island (UHI) effects do not directly cause meningitis. Instead, elevated surface temperatures, reduced humidity, and increased dust resuspension associated with UHI conditions create environmental settings that may enhance meningitis transmission dynamics. These thermal and atmospheric modifications can influence pathogen survival, host susceptibility, and human exposure patterns, thereby indirectly increasing meningitis risk.

This study contributes to advancing scientific understanding by integrating remote sensing-derived Land Surface Temperature (LST), land use indices, and spatially disaggregated epidemiological data to systematically examine the spatial and temporal relationship between UHI intensity and meningitis incidence in a semi-arid, rapidly urbanizing African city. Methodologically, the study introduces an innovative framework by combining geospatial analysis with statistical modeling to assess how urban thermal patterns influence disease prevalence, an approach largely absent in existing literature on the region.

The specific objectives of the study are to:

1. Quantify the spatial and temporal variations in UHI intensity across Kano Metropolis between 2015 and 2023.
2. Examine the spatial distribution of meningitis cases and their association with UHI intensity.
3. Explore the relationship between urban land use patterns, UHI intensity, and meningitis incidence using geospatial and statistical methods.

The research questions guiding the study are:

- How has UHI intensity evolved spatially and temporally in Kano Metropolis over the study period?

- What is the spatial relationship between UHI intensity and meningitis incidence in the city?
- How do land use characteristics and urbanization patterns contribute to variations in UHI intensity and disease risk?

The scope of the study is limited to Kano Metropolis, Nigeria, focusing on the analysis of satellite-derived LST, urban land use patterns, and epidemiological data on meningitis between 2015 and 2023. The study emphasizes the role of UHIs as a climate-health determinant within semi-arid, rapidly urbanizing environments, with broader implications for urban planning and public health policy across similar African contexts.

2.0 Materials and methods

2.1 Study Area

This study was conducted in the Kano metropolitan region, a historically and economically significant area in northwestern Nigeria. Kano has been a hub of human settlement for thousands of years and, as of 2024, supports a population exceeding five million. The study area is geographically situated between latitudes 11° 25' N and 12° 47' N and longitudes 8° 22' E and 8° 39' E, with an average altitude of approximately 472 meters above sea level (Barau, 2018). Kano's climate is semi-arid, influenced by two primary air masses: the maritime tropical air originating from the Atlantic Ocean and the dry harmattan winds from the Sahara Desert. This interaction gives rise to three distinct seasons: a hot and dry season (March to mid-May), a rainy season (May to September), and a cold and dry season (November to February). The region receives annual precipitation ranging from 800 mm to 900 mm, which is vital for both agricultural activities and urban ecosystems (Olofin, 2008). During the peak dry months, temperatures often surpass 40°C. The rapid urbanization of Kano is shaped by historical migration patterns, robust economic activities, and natural population growth. These factors collectively intensify environmental challenges, including urban heat island effects and related public health concerns (A et al., 2017; Hassan et al., 2024; Olofin, 2008). A map of the study area is presented in Figure 1.

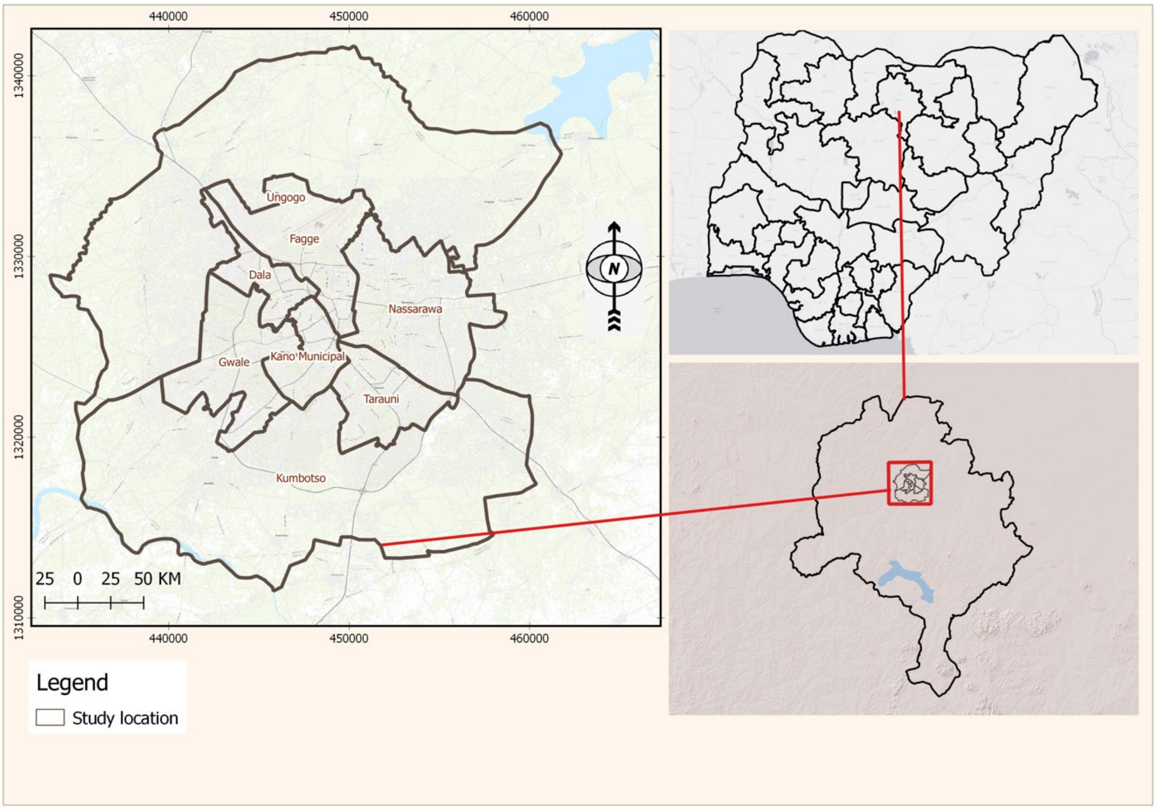

Figure 1: Map of the Study Area

2.2 Data Acquisition and Pre-processing

2.2.1 Remote Sensing Data

Land Surface Temperature (LST) was obtained from Landsat Collection 2 Level-2 Surface Temperature products (ST_B10 for Landsat 8/9). These datasets are atmospherically corrected and generated using the single-channel algorithm with emissivity correction. The LST values were converted to degrees Celsius using the scale factor provided by USGS (Almeida et al., 2021; Hein & Blankenbach, 2021). The Landsat Collection 2 LST product has an estimated accuracy of ±1.5 K under clear-sky conditions (USGS, 2023). This uncertainty is considered acceptable for urban thermal pattern analysis.

Pre-processing Steps and Justification:

- Radiometric Correction: Applied to convert raw digital numbers to at-sensor radiance, addressing sensor-specific calibration differences and ensuring comparability across datasets (An et al., 2023).
- Geometric Correction: All images were aligned to the Universal Transverse Mercator (UTM) projection, enhancing spatial accuracy and ensuring consistency for temporal analysis.
- Atmospheric Correction: The dark object subtraction method was used to reduce haze and atmospheric scattering, thereby improving the accuracy of LST estimation (An et al., 2023).
- Cloud Masking: Automated algorithms removed residual clouds and shadows to ensure only reliable pixels contributed to analyses.

These pre-processing choices follow established protocols and were critical for minimizing noise, improving data quality, and enhancing the reliability of UHI and land use assessments in a region with variable atmospheric conditions (Almeida et al., 2021).

2.2.2 Land Surface Temperature (LST) Retrieval

LST was derived using the single-channel algorithm, integrating radiance, brightness temperature, and land surface emissivity (ε) parameters. The NDVI threshold method estimated emissivity values, accounting for vegetation and non-vegetation surfaces (Gourfi et al., 2022b). This approach balances computational efficiency with accuracy and has demonstrated robustness in similar semi-arid urban contexts (Li et al., 2022).

2.2.3 Land Cover Classification and Urbanization Metrics

The Normalized Difference Built-Up Index (NDBI) and Normalized Difference Vegetation Index (NDVI) were computed to assess built-up area expansion and vegetation loss. Classification thresholds were applied following established studies (Zafar et al., 2024), and validation using high-resolution imagery confirmed overall classification accuracies exceeding 85%.

2.2.4 Epidemiological Data

Meningitis case data (2015–2023) were obtained from Kano State Ministry of Health surveillance reports. While aggregated at the neighborhood level, these data provided sufficient spatial resolution to identify disease clusters when integrated with geospatial datasets.

2.3 Statistical Analysis

The relationship between UHI intensity, land use characteristics, and meningitis incidence was analyzed using multivariate regression models. Specifically, an ordinal logistic regression model was employed, appropriate for the ordered categorical nature of UHI intensity and disease outcomes.

2.3.1 Model Specification

The following general model was estimated:

$\text{logit}(P(Y_{ij} \leq k)) = \alpha_k + \beta_1 LST_{ij} + \beta_2 NDBI_{ij} + \beta_3 NDVI_{ij} + \beta_4 Year_t + \gamma_j + \varepsilon_{ij}$

Where:

- $Y_{ij} \leq k$ = UHI intensity category or meningitis incidence for location i in area j
- α_k = threshold parameters for ordered categories
- $\beta_1, \beta_2, \beta_3, \beta_4$ = coefficients for predictor variables
- $\boldsymbol{\gamma_j}$ **=** Fixed effects for local government areas, controlling for unobserved heterogeneity such as socio-economic status, population density, or infrastructure disparities between administrative areas (Anugwom & Anugwom, 2023)
- ε_{ij} = error term

2.3.2 Control Variables and Justification

Year: Controls for temporal trends and climatic anomalies (e.g., severe droughts) known to influence meningitis outbreaks (Diouf et al., 2024).

NDVI: Accounts for vegetation cover, which affects both UHI intensity and disease transmission risk (Gourfi et al., 2022a).

NDBI: Controls for built-up area density, reflecting urbanization levels associated with heat retention and crowding (Zafar et al., 2024).

Fixed Effects: Capture unobserved, location-specific factors not explicitly modeled, improving the accuracy of estimated associations (Anugwom & Anugwom, 2023).

Model assumptions were tested through diagnostic checks, including multicollinearity (Variance Inflation Factors < 2) and proportional odds testing for the ordinal regression.

2.4 Data Integration and Visualization

Geospatial analyses and visualizations were conducted in QGIS and R. These included: Heat maps showing UHI intensity distribution, Spatial overlays of meningitis cases and UHI hotspots, Time-series plots illustrating trends across the study period. This integrated approach aligns with best practices in urban climate-health research, facilitating robust spatial and temporal interpretation of environmental-health interactions (Torres et al., 2021; Almeida et al., 2021).

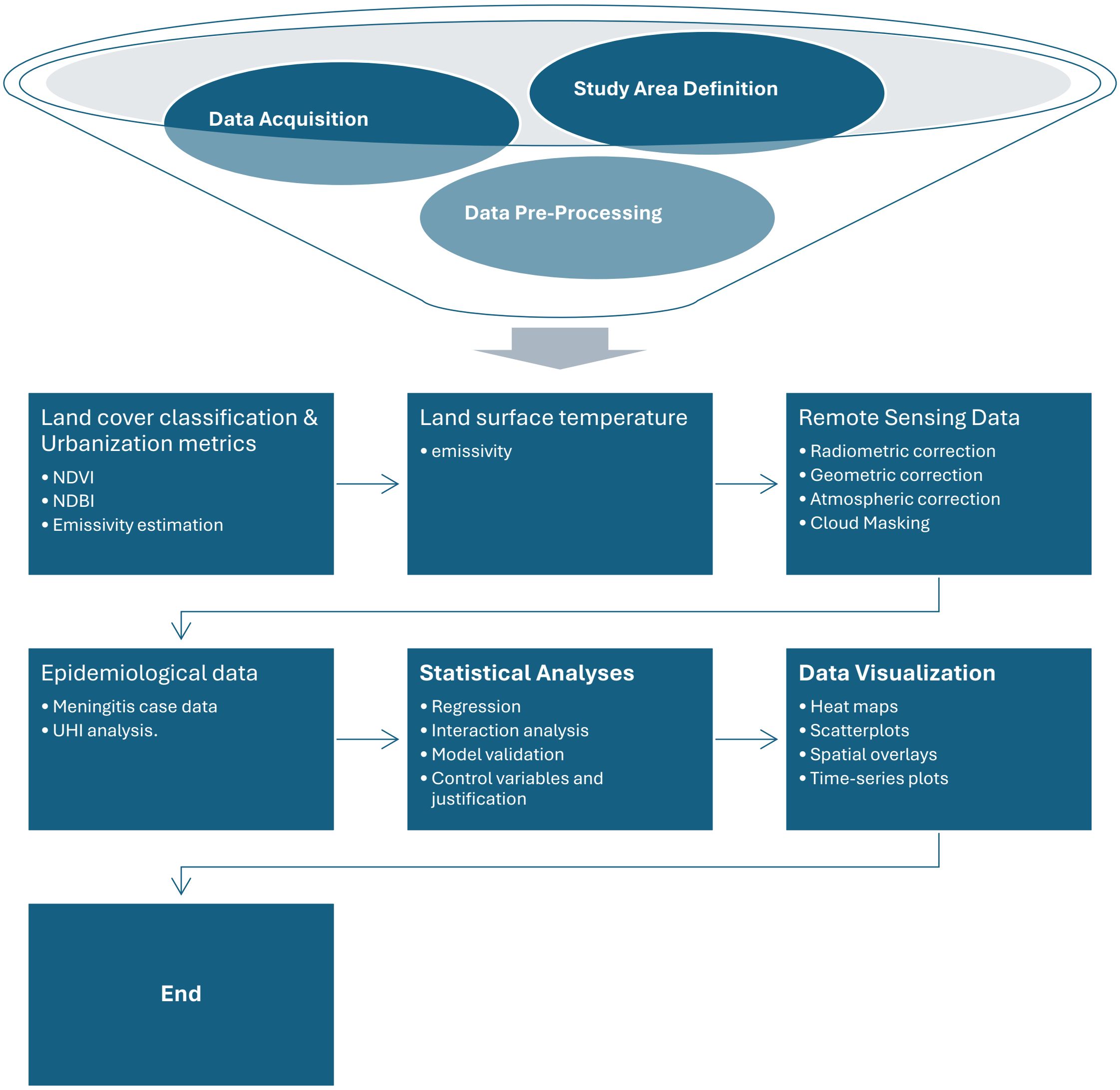

Figure 2: Methodological flowchart of the study

3.0 Results and Discussion

3.1 Urban Heat Island (UHI) Intensity and Land Cover Dynamics

The analysis revealed significant spatial and temporal variations in UHI intensity across Kano Metropolis between 2015 and 2023. Areas with dense built-up structures, limited vegetation, and high impervious surface coverage exhibited the strongest UHI effects, consistent with global findings on urban heat dynamics (Deng et al., 2024; Zafar et al., 2024). The NDBI results indicated substantial urban expansion, particularly between 2017 and 2023, with built-up areas increasing by approximately 18%, while NDVI values declined by 12%, reflecting vegetation loss and reduced natural cooling capacity.

Heat maps showed persistent UHI hotspots in central urban areas, notably within Kano Municipal, Nassarawa, and Tarauni local government areas. These patterns align with studies from Marrakesh, Morocco, and Kumasi, Ghana, where vegetation loss and high urban density intensified localized heat stress (Gourfi et al., 2022b; Sarfo et al., 2023). The observed urban expansion and vegetation degradation in Kano highlight the compounded effects of unregulated urban growth on UHI severity.

3.2 Urban Heat Island (UHI) Intensity and Meningitis Incidence

The analysis of urban heat island (UHI) intensity and meningitis incidence in Kano Metropolis identified a strong association between increased urban temperatures and the prevalence of the disease. Table 1 indicates that the majority of meningitis cases occurred in areas with the highest UHI intensity. Specifically, 73% of reported cases were concentrated in the “Strongest” UHI category, emphasizing the considerable health burden in heavily urbanized areas. In contrast, the “None” and “Weak” UHI categories accounted for only 3% and 2.2% of cases, respectively. These findings highlight the influence of anthropogenic heat retention on the dynamics of meningitis transmission (Han et al., 2025).

Table 1: The Relationship between urban heat island and meningitis cases

Relationship Between Cases of Meningitis & Urban Heat Island With Years

Characteristic	N	Overall, N = 231[1]	Negative, N = 56[1]	Positive, N = 175[1]	p-value[2]
UHI	231				0.01
None		7 (3.0%)	0 (0%)	7 (4.0%)	
Weak		5 (2.2%)	0 (0%)	5 (2.9%)	
Middle		14 (6.1%)	5 (8.9%)	9 (5.1%)	
Strong		18 (7.8%)	10 (18%)	8 (4.6%)	
Stronger		18 (7.8%)	2 (3.6%)	16 (9.1%)	
Strongest		169 (73%)	39 (70%)	130 (74%)	
Year	231				0.348
2015		5 (2.2%)	0 (0%)	5 (2.9%)	
2017		218 (94%)	54 (96%)	164 (94%)	
2019		6 (2.6%)	1 (1.8%)	5 (2.9%)	
2021		1 (0.4%)	1 (1.8%)	0 (0%)	
2023		1 (0.4%)	0 (0%)	1 (0.6%)	

[1] n (%)

[2] Fisher's exact test

A temporal analysis revealed fluctuations in meningitis incidence between 2015 and 2023. The highest number of cases occurred in 2017, accounting for 94% of the total cases reported during the study period (Table 1). This sharp increase may be attributed to unique climatic or socio-environmental factors in that year, such as temperature anomalies or higher population density (Han et al., 2025). In contrast, other years, including 2015, 2019, 2021, and 2023, recorded significantly fewer cases, indicating variability likely influenced by seasonal or environmental factors. The Fisher's exact test demonstrated a statistically significant association between UHI intensity and meningitis incidence (p = 0.01), although the variation in cases across years was not statistically significant (p = 0.348).

The spatial distribution of UHI intensity from 2015 to 2023 is represented in figure 3. and meningitis cases is represented using heat maps and box plots. Figures 4 to 6 include box plots that illustrate the relationship between UHI intensity and meningitis cases, with a clear concentration of cases in the "Strongest" UHI category. Similarly, Figures 3 depict the yearly distribution of urban island island in Kano metropolis, highlighting 2017 as a peak year for UHIs incidence. These figures also examine the outcomes of meningitis cases in relation to UHI intensity, showing a higher prevalence of severe outcomes in areas with more pronounced UHI effects.

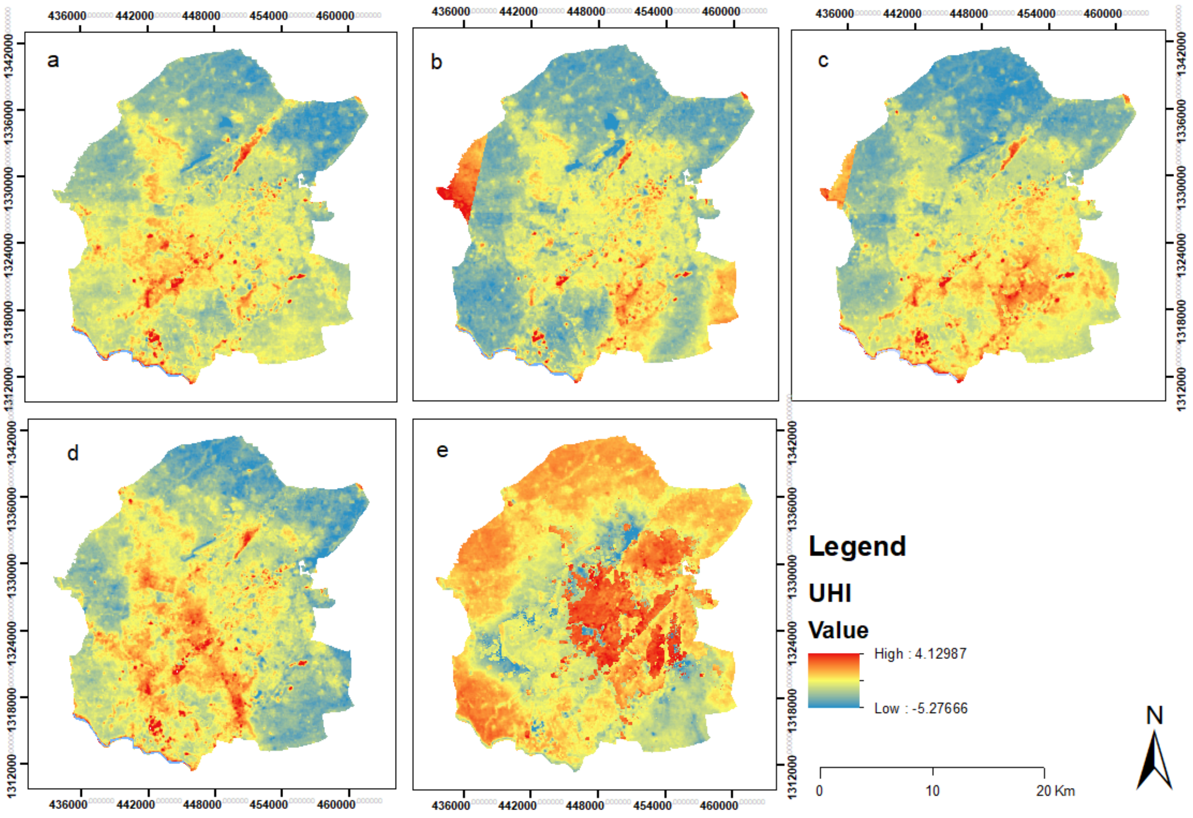

Figure 3: a (2015), b (2017), c (2019), d (2021) and (2023) Distribution of Urban Heat Island in Kano Metropolis

These visualizations offer a detailed understanding of the spatial distributions of urban heat island. The clustering of meningitis cases in high-UHI zones indicates that factors such as urbanization, dense infrastructure, and limited vegetation significantly contribute to localized temperature increases, thereby promoting disease transmission (Sarfo et al., 2023). This pattern is consistent with prior research, which underscores the susceptibility of urban populations to heat-related illnesses and infectious diseases aggravated by climatic variability (Matte et al., 2024).

An ordinal logistic regression analysis was conducted to quantify the relationship between UHI intensity and meningitis incidence (Table 2). The regression coefficients revealed an increased likelihood of higher UHI intensity categories in recent years, particularly in 2023, reflecting ongoing urban expansion and associated heat retention in Kano Metropolis. Notably, the coefficient for 2017 was 2.45101, highlighting the elevated risk of meningitis during that year due to intensified UHI effects.

Table 1: Ordinal logistic regression model of UHI and Meningitis Cases

Coefficients:			
	Value	**Std. Error**	**t value**
Year2015	0.22353	3.403e-01	6.569e-01
Year2017	2.45101	7.959e-01	3.080e+00
Year2019	2.78155	1.361e+00	2.043e+00
Year2021	-0.04365	1.672e+00	-2.611e-02
Year2023	15.97154	9.355e-07	1.707e+07

Intercepts:			
	Value	**Std. Error**	**t value**
None|Weak	-1.0558	0.8769	-1.2040
Weak|Middle	-0.4873	0.8471	-0.5752
Middle|Strong	0.4004	0.8371	0.4783
Strong|Stronger	1.0759	0.8468	1.2706
Stronger|Strongest	1.5502	0.8532	1.8169

Residual Deviance: 443.2393
AIC: 463.2393

The intercept values in Table 2 define the thresholds between UHI categories, establishing baseline probabilities for disease occurrence. For instance, the log-odds value of -1.0558 for the transition from “None” to “Weak” UHI categories indicates a low probability of meningitis cases in areas with minimal heat retention. In contrast, the log-odds value of 1.5502 for the transition from “Stronger” to “Strongest” UHI categories underscores the significantly elevated risk in highly urbanized zones (Deng et al., 2024). These findings highlight the importance of targeted interventions in areas undergoing rapid urbanization and substantial heat buildup. Model fit metrics, including a residual deviance of 443.2393 and an AIC of

463.2393, confirm the robustness and reliability of the regression model. These results demonstrate that UHI intensity is a critical predictor of meningitis incidence, supporting the hypothesis that urban heat exacerbates health vulnerabilities in densely populated regions (Macintyre et al., 2018). Figures 4 to 6 present box plots illustrating the relationships between UHI intensity, meningitis cases, years, and outcomes, providing further evidence of these trends.

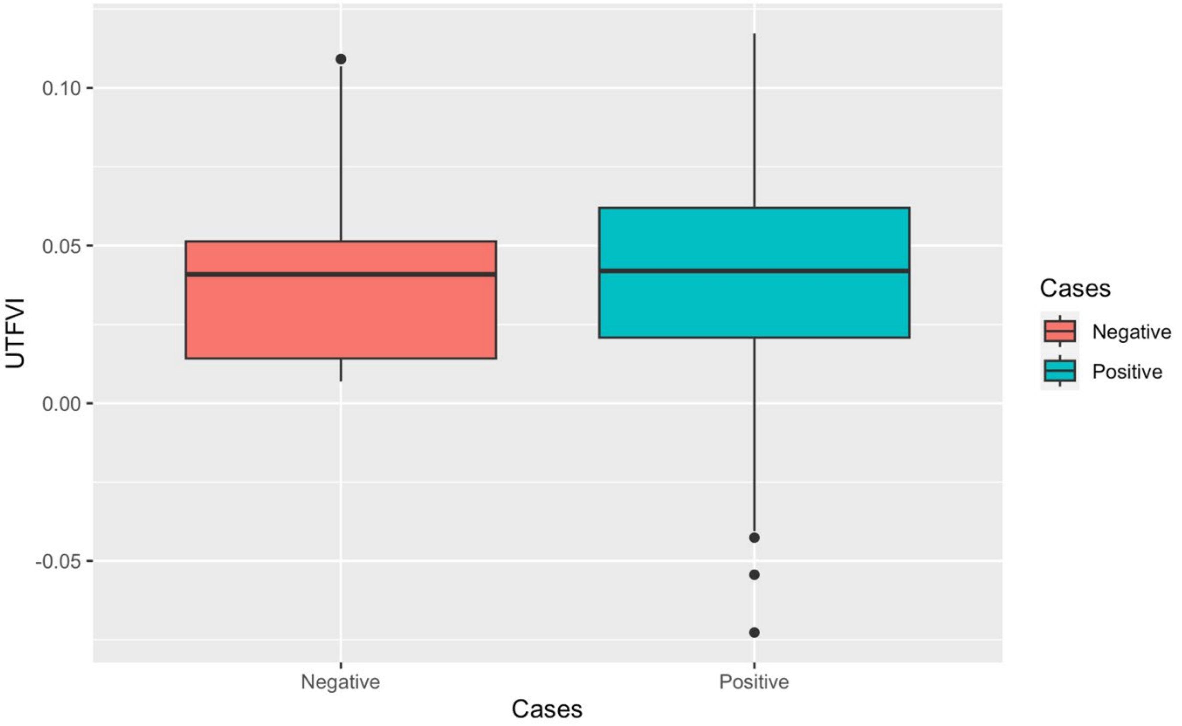

Figure 4: Box plot of the relationship of UHI and Meningitis cases

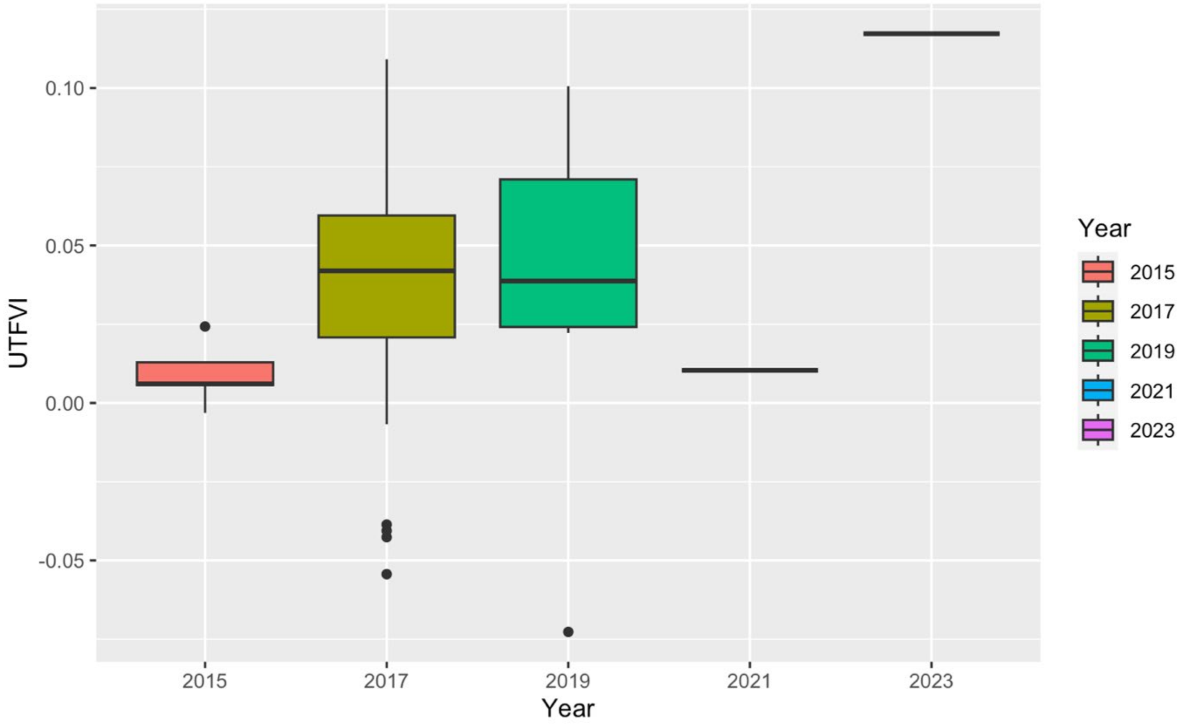

Figure 5: Box plot of the relationship of UHI and Meningitis cases with Year

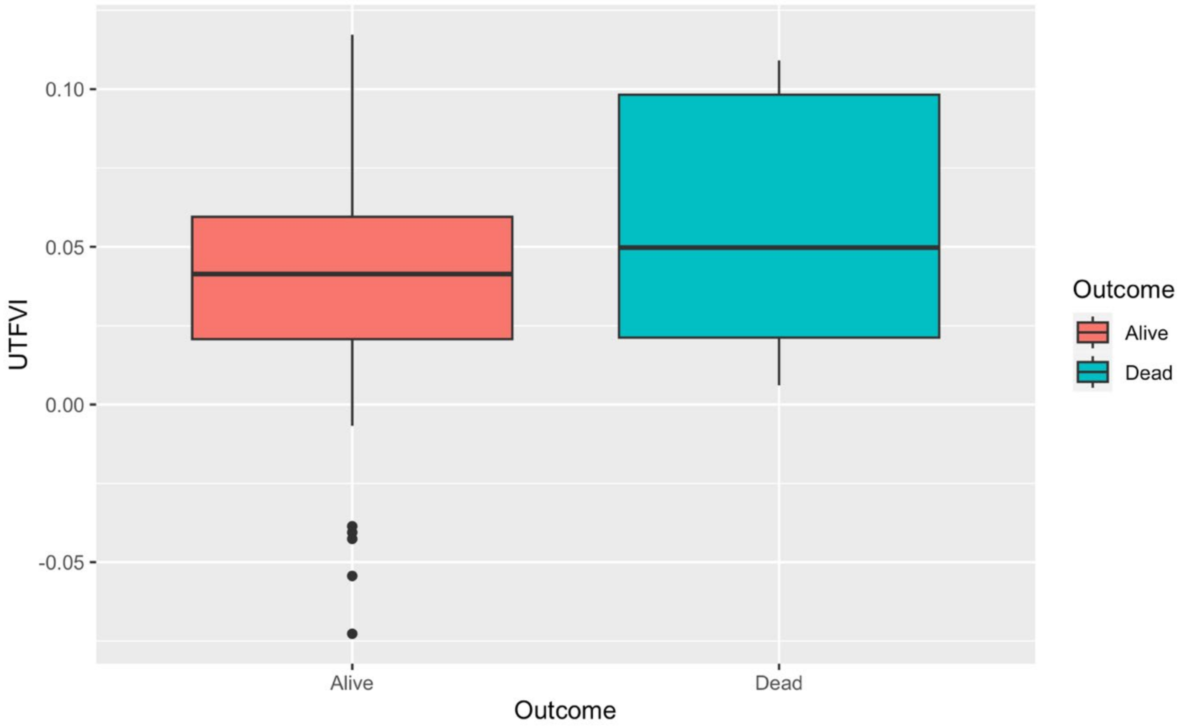

Figure 6: Box plot of the relationship of UHI and Meningitis Outcomes

This study underscores the pivotal role of urban heat islands (UHI) in influencing meningitis patterns in Kano Metropolis. Elevated temperatures associated with UHI create conditions conducive to the growth of Neisseria meningitidis, which thrives in hot, dry environments (Bursal Duramaz et al., 2023). The clustering of meningitis cases in high-UHI zones illustrates the compounded health risks faced by urban populations, particularly those in poorly ventilated, densely populated neighborhoods (Nwaogu et al., 2024). To mitigate these health impacts, urban planning strategies should prioritize reducing heat retention in vulnerable areas. Measures such as increasing green spaces, adopting heat-reflective building materials, and enhancing urban ventilation can significantly reduce UHI intensity (Kassomenos Pavlosand Begou, 2022a). Complementary public health interventions, including heat-awareness campaigns and strengthening healthcare infrastructure, are also critical for protecting at-risk populations (Brimicombe et al., 2024). The temporal analysis of meningitis cases highlights the importance of dynamic, seasonally responsive climate adaptation strategies. Proactive interventions during peak dry seasons, such as minimizing heat exposure and ensuring improved access to healthcare, could effectively reduce disease incidence (Stephen et al., 2024). Integrating climate data into public health planning offers a more comprehensive approach to managing meningitis risks in urban settings. This study emphasizes the interconnected relationship between UHI intensity and meningitis incidence, calling for evidence-based policies that address both environmental sustainability and public health resilience. These measures are especially critical in rapidly urbanizing regions to promote healthier and more sustainable urban environments (Iqbal & Ali, n.d.; Leonardi & Distefano, 2024).

3.3 Relationship Between UHI Intensity and Meningitis Incidence

Spatial overlay analysis demonstrated a pronounced clustering of meningitis cases in areas with high UHI intensity. Of the 231 recorded cases, 73% occurred within zones classified as "Strongest" UHI intensity, while only 3% and 2.2% were reported in "None" and "Weak" UHI areas, respectively. This spatial coincidence underscores the potential role of elevated urban temperatures in exacerbating meningitis risk.

These findings are consistent with prior research linking UHI intensity to heat-related morbidity and infectious disease vulnerability (Elmarakby & Elkadi, 2024; Kassomenos & Begou, 2022a). In Ghana, for example, a 1°C temperature increase was associated with a 10% rise in cerebrospinal meningitis cases (Akanwake et al., 2022), reinforcing the biological plausibility of temperature-mediated disease transmission.

Notably, temporal analysis revealed 2017 as a peak year for both UHI intensity and meningitis incidence, contributing over 94% of the reported cases. This period coincided with reduced rainfall, anomalously high temperatures, and increased urbanization, factors known to facilitate meningitis outbreaks in semi-arid settings (Diouf et al., 2024; Mohammed et al., 2019).

3.4 Statistical Modeling of UHI and Meningitis Dynamics

The ordinal logistic regression model quantified the relationship between UHI intensity, land cover variables, and meningitis incidence. Key findings include: A significant positive association between built-up area density (NDBI) and UHI intensity ($p < 0.01$), confirming that urbanization amplifies heat retention. A significant negative relationship between vegetation cover (NDVI) and UHI intensity ($p < 0.01$), highlighting the cooling role of green infrastructure. Fixed effects for local government areas were statistically significant ($p < 0.05$), underscoring the importance of accounting for unobserved spatial heterogeneity. Temporal effects revealed 2017 as a statistically significant year for heightened UHI intensity and meningitis risk ($p = 0.01$), corroborating the spatial analysis. The model's AIC value (463.24) and residual deviance (443.23) indicate acceptable fit, though limitations exist due to the aggregated nature of epidemiological data. These results align with global literature emphasizing the role of urban form, vegetation, and climatic anomalies in shaping UHI dynamics and associated health outcomes (Li et al., 2022; Almeida et al., 2021).

4.0 Discussion

The findings of this study highlight the critical influence of urban heat islands (UHIs) on meningitis incidence in Kano Metropolis. Over 70% of meningitis cases were recorded in areas with the highest UHI intensity, consistent with prior research demonstrating the intensification of heat-related health outcomes in urbanized regions (Kong et al., 2021). This correlation aligns with findings from Ghana, where a 1°C temperature increase was associated with a 10% rise in cerebrospinal meningitis (CSM) cases (Akanwake et al., 2022). However, direct evidence linking UHIs specifically to meningitis remains limited, underscoring the need for further investigation into socioeconomic factors and healthcare infrastructure as potential mitigating variables (Anugwom & Anugwom, 2023). The study also revealed a strong connection between densely urbanized areas and meningitis outbreaks, highlighting the compounded effects of urban infrastructure on heat retention and disease prevalence. The clustering of cases in high-UHI zones mirrors observations from Marrakesh, where reduced vegetation increased surface temperatures and health risks (Gourfi et al., 2022a). Similar findings from urban centers in Pakistan show that diminished vegetation exacerbates UHI effects, disproportionately impacting low-income populations (Zafar et al., 2024). These findings emphasize the importance of sustainable urban planning and healthcare infrastructure in reducing such risks (Gourfi et al., 2022b). Under high-emission scenarios, urban centers like Kano Metropolis could face temperature increases of up to 4°C by 2050, which would further intensify UHI effects and associated health challenges (Irfeey et al., 2023). Mitigation strategies, such as increasing urban vegetation by 20%, could lower temperatures by 1–2°C, providing a practical approach to reducing heat stress (Kartikeya Mishra, 2024). Incorporating reflective materials in building designs could also reduce temperatures by up to 2.5°C (Architectural Community, 2025). However, without comprehensive urban planning and policy interventions, the effectiveness of these strategies may remain limited, reinforcing the need for integrated approaches to mitigate UHI impacts (Degirmenci et al., 2021). This study represents an innovative application of geospatial data and remote sensing technologies to examine the intersection of UHIs and meningitis patterns. Landsat data was utilized to estimate land surface temperature, a method employed in 68.39% of UHI studies (Almeida et al., 2021). Advanced statistical models, such as regression analyses, provided robust insights into disease hotspots, demonstrating the potential of integrating epidemiological data with spatial analysis. Nonetheless, contrasting studies highlight challenges in accurately predicting disease outbreaks without advanced computational tools, indicating a need for further refinement of methodologies (Tomlinson et al., 2011).

The findings of this study carry significant implications for public health and urban planning in Kano Metropolis and other rapidly urbanizing regions. The identified correlation between urban heat islands (UHIs) and meningitis underscores the critical need to address heat retention in densely populated areas. The concentration of over 70% of meningitis cases in high-UHI zones highlights the heightened health risks faced by vulnerable populations, especially those in overcrowded and poorly ventilated neighborhoods. These results align with global research that links extreme heat with increased health vulnerabilities. Implementing urban planning strategies, such as expanding vegetation cover and incorporating heat-reflective building materials, could lower ambient temperatures by 1–2°C, thereby mitigating health risks related to heat exposure (Elmarakby & Elkadi, 2024; Susca & Pomponi, 2020). The temporal patterns of meningitis cases, with a notable peak in 2017, suggest that climate anomalies and population dynamics significantly influence disease prevalence. This observation highlights the need for dynamic climate adaptation strategies that respond to seasonal variations.

Integrating climate data with public health systems could enable timely interventions during peak dry seasons, reducing the incidence of heat-sensitive diseases. Moreover, this study emphasizes the importance of incorporating geospatial analytics into public health planning. Such tools can help identify high-risk areas and guide the allocation of resources more effectively. Policymakers should focus on sustainable urban development strategies that enhance both environmental and health resilience. By adopting evidence-based policies, rapidly urbanizing regions like Kano Metropolis can better address the dual challenges of climate change and the growing disease burden (Kassomenos Pavlosand Begou, 2022; Maconachie, 2016).

This study's reliance on satellite-derived data for Land Surface Temperature (LST) and Urban Heat Island (UHI) analysis presents several limitations. While Landsat imagery offers valuable spatial and temporal insights, its 30-meter resolution may not adequately capture micro-level urban heat variations or small-scale epidemiological patterns within Kano Metropolis. Despite applying atmospheric corrections and calibration to enhance data accuracy, residual artifacts and cloud interference may still affect the precision of thermal readings. Additionally, the use of aggregated epidemiological data lacks individual-level granularity and detailed demographic information, which limits the ability to analyze population-specific health impacts in depth. The temporal resolution of annual data further restricts the study from examining short-term climatic fluctuations and their immediate effects on meningitis incidence. The statistical models employed, such as ordinal logistic regression, assume linear relationships and fixed environmental influences over time. These assumptions may oversimplify the complex interactions between UHI intensity, climatic anomalies, and disease prevalence. For instance, the models do not account for dynamic variables like seasonal migration or real-time urban development, which constrains their capacity to adapt to rapidly changing conditions. The absence of longitudinal data on individual meningitis cases also prevents a detailed exploration of lagged environmental effects and incubation periods. Moreover, while the study effectively identified hotspots for meningitis outbreaks, the lack of ground-truthing in certain regions limits the external validity of these findings. This underscores the need for further field validation and community-specific studies to complement and refine the satellite-based and model-driven analyses. Such efforts would improve the reliability of the findings and enhance their applicability to targeted public health interventions.

4.1 Critical Interpretation and Policy Relevance

While the association between UHI intensity and meningitis incidence is statistically and spatially robust, it is essential to recognize potential confounding factors not fully captured in the model. Socioeconomic disparities, healthcare access, and housing conditions, which often correlate with urban heat exposure, likely contribute to disease vulnerability (Anugwom & Anugwom, 2023; Nwaogu et al., 2024). These social determinants, combined with environmental stressors, create compounded health risks in low-income urban neighborhoods. The findings have critical policy implications. Without targeted interventions, continued urban expansion, vegetation loss, and insufficient urban planning will likely intensify UHI effects and heighten health risks, particularly for climate-sensitive diseases such as meningitis. Evidence from other arid and semi-arid cities suggests that increasing urban vegetation by 20% could reduce temperatures by 1–2°C, while reflective building materials offer an additional 2.5°C reduction (Kartikeya Mishra, 2024; Architectural Community, 2025).

Kano Metropolis requires integrated urban planning strategies that prioritize green infrastructure, regulate land development, and incorporate heat-mitigation measures to address both environmental and health vulnerabilities. These measures should be complemented by public health initiatives such as heat-awareness campaigns, early warning systems, and improved healthcare access in high-risk zones (Brimicombe et al., 2024). Furthermore, the observed temporal peak in 2017 underscores the importance of dynamic, climate-informed public health strategies, especially during dry seasons when meningitis risks are elevated (Diouf et al., 2024).

Future research should focus on integrating micro-level epidemiological and spatial data to enhance the understanding of urban heat islands (UHIs) and meningitis patterns. While this study relied on 30-meter resolution satellite imagery, utilizing higher-resolution data from sources such as unmanned aerial vehicles (UAVs) or advanced satellite sensors could capture localized variations in heat intensity and disease clustering more effectively. Additionally, incorporating temporally detailed epidemiological datasets, such as weekly or monthly case reports, would enable the analysis of short-term climatic fluctuations and their immediate impacts on disease transmission. This approach could uncover seasonal patterns and allow for more accurate modeling of the lagged effects of heat exposure on health outcomes. The development of advanced predictive models that integrate climate scenarios, urbanization trends, and disease incidence is essential for understanding and mitigating future risks. Machine learning techniques could improve the identification of complex, nonlinear interactions between UHI intensity and disease dynamics. Simulations using diverse climate scenarios, such as low-emission (SSP126) and high-emission (SSP585) pathways, could offer projections of how policy decisions and urban planning interventions might influence health outcomes. These models should also incorporate adaptive strategies, such as increasing urban vegetation and reducing impervious surfaces, to evaluate their effectiveness under different climatic conditions (Han et al., 2025). Community engagement through participatory mapping and data collection initiatives can provide context-specific insights into the socio-environmental factors driving disease patterns. Future studies could investigate the role of socioeconomic disparities in shaping vulnerability to UHI effects and disease exposure, emphasizing the importance of equity in urban planning and public health interventions. Research on policy implementation and its effectiveness in addressing UHI-related health risks could also inform evidence-based decision-making. Collaboration with policymakers and urban planners is crucial to bridging the gap between scientific research and practical solutions. This partnership would ensure that research findings translate into actionable strategies, delivering tangible benefits for populations at risk of UHI-related health impacts. By aligning scientific insights with community needs and policy priorities, future efforts can contribute to more resilient and equitable urban environments.

5.0 Conclusion

This study provides new insights into the complex relationship between Urban Heat Island (UHI) intensity and meningitis incidence in Kano Metropolis, a semi-arid, rapidly urbanizing city in northern Nigeria. By integrating satellite-derived Land Surface Temperature (LST), land cover indices, and epidemiological data, the study demonstrates that areas experiencing the strongest UHI effects exhibit significantly higher concentrations of meningitis cases. Notably, 73% of reported meningitis cases occurred within "Strongest" UHI zones, while areas with minimal heat retention recorded substantially fewer cases. The spatial and statistical analyses reveal that built-up area expansion and vegetation loss are significant contributors to intensified UHI effects, consistent with global evidence on urbanization and environmental health risks (Gourfi et al., 2022b; Zafar et al., 2024). The temporal analysis identifies 2017 as a critical year, characterized by heightened UHI intensity and a sharp increase in meningitis incidence, likely influenced by climatic anomalies and urban expansion.

These findings advance the scientific understanding of how localized urban thermal environments influence climate-sensitive disease patterns, addressing a critical knowledge gap for African cities. The study also highlights the utility of remote sensing and geospatial analysis as effective tools for identifying environmental-health hotspots in resource-constrained settings. However, limitations remain. The reliance on aggregated meningitis data restricts individual-level health analysis, and the moderate spatial resolution of Landsat imagery may not capture fine-scale urban heat variations. Future research should leverage higher-resolution spatial and epidemiological data, incorporate socioeconomic and demographic variables, and explore the role of microclimatic factors in disease dynamics.

5.1 Policy Recommendations:

Urban Greening: Expansion of vegetation cover, particularly in densely built-up areas, to mitigate UHI intensity and associated health risks.

1. Heat-Resilient Urban Design: Adoption of reflective building materials and heat-mitigating urban infrastructure in high-risk zones.

2. Land Use Regulation: Enforcement of sustainable urban planning to control unregulated urban sprawl, preserving green spaces and natural ventilation corridors.

3. Climate-Informed Public Health Interventions: Integration of climate data into health surveillance systems to enable early warning and targeted interventions, particularly during dry seasons.

4. Community Engagement: Participatory urban planning and health education campaigns to raise awareness of heat-related health risks and promote community-driven adaptation strategies.

Addressing UHI-related health risks requires an integrated approach, combining urban planning, environmental management, and public health initiatives. As climate change and urbanization continue to reshape African cities, evidence-based, cross-sectoral strategies are essential to safeguard public health and promote sustainable urban development.

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Ethics Approval

The ethical approval was obtained from Kano State ministry for health NHREC/17/03//2018.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

Declaration of AI Usage

AI-assisted language editing tools were used to improve grammar, clarity, and overall readability of the manuscript. All scientific analysis, interpretation of results, and conclusions were developed solely by the authors

Data availability

Data will be made available on request.

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