VOL. 23 | NO. 1 | ISSUE 89 | JAN.-MARCH 2025

A Spatial Model of Socioeconomic and Demographic Determinants of *Dengue* Hemorrhagic Fever in Nepal

Mahato RK,[1] Htike KM,[1] Yadav A,[2] Baral S,[3] Yadav RK,[3,4] Kafle A,[5] Sharma V[6]

[1]Faculty of Public Health,
Khon Kaen University,
Khon Kaen, Thailand.

[2]Ministry of Health and Population,
Kathmandu, Nepal.

[3]School of Health and Allied Sciences, Pokhara University, Pokhara, Nepal

[4]LA GRANDEE International College,
Department of Public Health,
Pokhara University, Nepal.

[5]Tropical Medicine, Faculty of Medicine,

Khon Kaen University, Thailand.

[6]Kathmandu University School of Medical sciences,
Dhulikhel, Nepal.

Corresponding Author

Roshan Kumar Mahato
Faculty of Public Health,
Khon Kaen University,
Khon Kaen, Thailand.

E-mail: roshan@kku.ac.th

Citation

Mahato RK, Htike KM, Yadav A, Baral S, Yadav RK, Kafle A, et al. A Spatial Model of Socioeconomic and Demographic Determinants of *Dengue* Hemorrhagic Fever in Nepal. *Kathmandu Univ Med J.* 2025; 89(1): 25-34.

ABSTRACT

Background

Dengue hemorrhagic fever (DHF) has re-emerged across the global South, particularly in tropical and subtropical urban areas, driven by environmental changes alongside local demographic and socioeconomic factors.

Objective

To investigate the spatial patterns and socioeconomic determinants of dengue fever in Nepal from 2020 to 2023.

Method

Using Geographic Information Systems (GIS), Gi* cluster analysis, and Local Moran's I statistics, the study examined the relationship between socio-economic variables and dengue incidence across districts. Key factors analyzed included population density, urbanization, and night-time light (NTL) intensity.

Result

Bivariate Local Indicators of Spatial Association (LISA) analysis showed fluctuating correlations between dengue hemorrhagic fever incidence and factors such as population density, urbanization, and night-time light intensity. Moran's I value for population density were -0.083 in 2020, -0.082 in 2021, 0.526 in 2022, and -0.020 in 2023. Similarly, for urbanization, Moran's I values shifted from -0.103 in 2020 to -0.090 in 2021, 0.458 in 2022, and 0.007 in 2023. Night-time light intensity also demonstrated changing correlations, with Moran's I values of -0.091 in 2020, -0.102 in 2021, 0.415 in 2022, and -0.068 in 2023. A notable shift from negative to positive correlations occurred between 2020 and 2022. In 2022, high-incidence dengue hemorrhagic fever clusters emerged in densely populated areas, while distinct spatial patterns were observed in 2020 and 2021.

Conclusion

Dengue hemorrhagic fever risk spatial models are useful tools for detecting high-risk locations and driving proactive public health initiatives. The study emphasized the importance of dynamic, targeted public health interventions based on spatial and socio-economic factors to effectively manage evolving dengue outbreak patterns.

KEY WORDS

Dengue, Gi statistics, Local indicators of spatial association, Socio-economic status, Spatial analysis*

INTRODUCTION

Dengue fever is a significant health concern in tropical regions, particularly in densely populated urban areas where mosquitos thrive.[1] The global incidence has surged, with over 6.5 million cases and 7,300 deaths reported in 2023.[2-4] In Southeast Asia, dengue causes economic burdens, with annual losses of up to $1.38 billion and 214,000 disability-adjusted life years (DALYs).[5-7] Nepal has seen a rapid rise in dengue cases, recording an unprecedented 54,784 cases and 88 deaths in 2022, primarily in urban districts like Kathmandu, Bhaktapur, and Lalitpur.[8] Dengue transmission peaks during the monsoon season, from June to September.[9] Nepal's response includes vector control measures, such as larvicides, space spraying, and promoting behavioral changes like mosquito net use.[10,11] Spatial analysis is vital in identifying dengue hotspots and guiding public health interventions.[12,13] By mapping case distributions and examining socio-economic factors, it enables real-time surveillance and targeted responses.[14,15] This study aimed to examine the spatial model of Nepal's sociodemographic and socioeconomic factors associated with dengue incidence from 2020 to 2023, contributing to more effective prevention and management strategies.

METHODS

Nepal, situated between India and the Tibet Autonomous Region of China, covers an area of 147,181 square kilometres, stretching 885 km from east to west and 193 km from north to south. As of the 2021 census, the country's population stands at approximately 29 million, including 2.2 million people living abroad, with an annual growth rate of 0.92%.[16] Nepal is located between latitudes 26°22′ N and 30°27′ N, and longitudes 80°4′ E and 88°12′ E. Administratively, the country is divided into 7 provinces and 77 districts, which help manage governance across the diverse landscape.[17]

Nepal's geography ranges from the fertile plains of the Gangetic region to the towering Himalayas. The Upper Himalaya, accounting for 15% of the land area, is home to eight of the world's highest peaks, attracting mountaineers and trekkers. The Middle Hills and Lower Himalayas, covering 68% of the country, have a temperate climate and rich soil, and include the capital, Kathmandu, along with other major cities. The Tarai Region, which occupies 17% of the land, is an agriculturally productive area and also contains important wildlife reserves. Nepal experiences a wide range of climates, with temperatures in the Tarai reaching up to 45°C, while in the Himalayas, temperatures can drop below -30°C. Kathmandu, on the other hand, enjoys relatively mild weather throughout the year.[18]

The origin of the variables

This study utilized multiple data sources to analyze a range of socio-economic variables. Data on average household size, annual growth rate (%), population density, and the percentage of owned versus rented houses was obtained from the National Report of Nepal's National Population and Housing Census 2021.[19] Data on dengue cases was sourced from the Nepal Epidemiology and Disease Control Division (EDCD) under the Ministry of Health and Population, Nepal.[20]

Data Analysis: Spatial analysis

The data was imported into Quantum GIS (QGIS) version 3.36 after being processed, validated, and cleaned to merge spatial and non-spatial information, generating a shapefile for analysis. Using QGIS, we visualized dengue incidence from 2020 to 2023, aiming to identify patterns and possible clusters of high incidence rates. A detailed spatial analysis was then carried out with GeoDa version 1.22.[21]

Gi statistics

The Getis-Ord Gi* statistic was employed in the data analysis to identify spatial clusters of dengue incidence across Nepal's districts from 2020 to 2023. This spatial analysis technique detected statistically significant hotspots (clusters of high dengue cases) and cold spots (clusters of low dengue cases) by comparing the observed dengue cases in a district with those in neighboring districts. The Gi* statistic calculated whether the spatial concentration of dengue cases in a given district and its neighbors was significantly higher or lower than the expected average.[22]

Getis-Ord Gi* statistic was computed the following formula.

$$Gi^* = (\sum_j \omega_{ij} \chi_j)/(\sum_j \chi_j)$$

Where the weights are determined by ω_{ij}, and the normalization is done by dividing by the total sum of χ_j values.

A weight matrix was defined using the 3 K-nearest neighbors, which established neighboring relationships based on geographically closest districts. Districts that exhibited significantly higher incidence rates than expected, relative to their neighbors, were identified as hotspots, while districts with lower-than-expected incidence rates were labeled as cold spots. By applying the Gi* statistic, spatial patterns of dengue transmission were uncovered, highlighting regions with persistently high or low disease incidence and providing insights into where targeted public health interventions would have been most effective.[23]

Local Indicators of Spatial Association (LISA)

Local Moran's I was computed using the equation:

$$I_1 = \frac{Z_i}{S_1} * Z_j W_{ij}$$

where "n" is the total number of regions, "S0" is the sum of spatial weights, "Z" represents the variable's deviation from its mean, "S1" is the sum of squared deviations, and "Wij" refers to the spatial weight between regions i and j.

Spatial autocorrelation for this study was evaluated using Local Indicators of Spatial Association (LISA), a set of statistics that includes measures like Moran's I to detect various spatial patterns.[24] We applied LISA to assess the global spatial autocorrelation of dengue incidence and related factors. Specifically, Moran's I was used within the LISA framework to identify whether particular regions formed part of spatial clusters with similar dengue incidence values (such as high-high or low-low clusters) or if they were outliers (like high-low or low-high clusters). A weight matrix with three clusters of K-nearest neighbours was employed for both univariate and bivariate analysis. This study used 999 permutations to assess the sensitivity of significant locations to the number of permutations, with a significance threshold set at $p < 0.05$.

The Khon Kaen University Ethics Committee for Human Research (KKUEC) has granted an exemption for ethical approval for this study (Reference Number: HE 672162).

RESULTS

Geographic Distribution of Dengue Incidence

In 2020, a marked increase in dengue incidence was recorded in the districts of Baitadi, Doti, Dailekh, Baglung, Dolpa, and Mustang, while it was lower in Mugu, Jumla, and Sindhupalchok. The following year, 2021, recorded high dengue incidence in Dolpa, Mustang, and Baglung, with lower rates in Jumla, Rukum West, Rautahat, Sunsari, and Morang. In 2022, districts such as Parsa, Makawanpur, Kathmandu, Lalitpur, Bhaktapur, Kabhrepalanchok, Nuwakot, and Sindhupalchok experienced high dengue incidence, whereas Bajura, Mugu, Kalikot, Jumla, Salyan, Dang, and Siraha saw lower incidence rates. Finally, in 2023, high dengue incidence was reported in Taplejung, Bhojpur, Dhankuta, Nuwakot, Gorkha, Lamjung, Chitawan, and Nawalpur, while Achham, Bardiya, Banke, Dang, Mugu, Sarlahi, Mahottari, Dhanusha, and Bara districts had lower rates (Table 1 and Fig. 1).

Table 1. Gi* cluster map of Dengue incidence in 2020-2023

Dengue Clusters	Gi* statistics	
	High	Low
2020	Baitadi*	Mugu***
	Doti*	Jumla*
	Dailekh*	Sindhupalchok*
	Baglung**	
	Dolpa*	
	Mustang*	
2021	Dolpa*	Jumla***
	Mustang*	Rukum West***
	Baglung**	Rautahat*
		Sunsari*
		Morang*
2022	Parsa*	Bajura*
	Makawanpur***	Mugu*
	Kathmandu***	Kalikot*
	Lalitpur***	Jumla*
	Bhaktapur**	Salyan*
	Kabhrepalanchok***	Dang*
	Nuwakot **	Siraha*
	Sindhupalchok*	
2023	Taplejung**	Achham*
	Bhojpur*	Bardiya*
	Dhankuta*	Banke*
	Nuwakot*	Dang*
	Gorkha*	Mugu**
	Lamjung*	Sarlahi**
	Chitawan*	Mahottari*
	Nawalpur*	Dhanusha*
		Bara*

P-value 0.05*, 0.01**, 0.001***

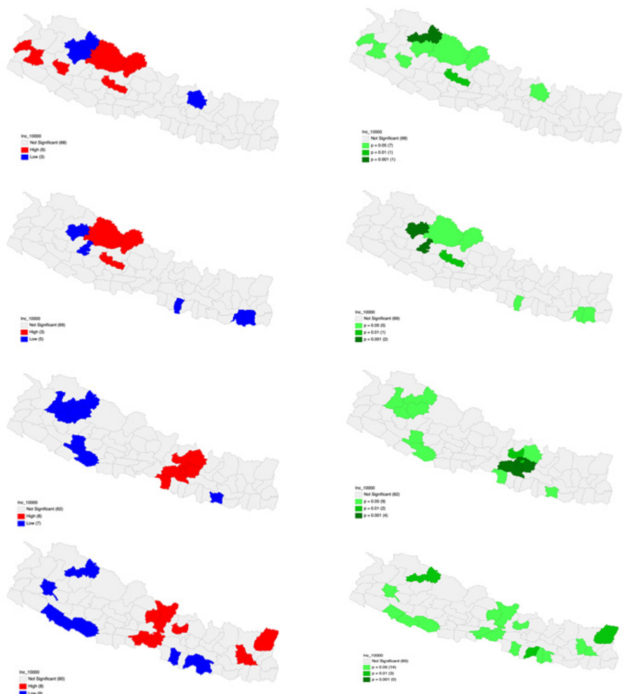

Figure 1. Gi* Cluster map of Dengue incidence in Nepal 2020-2023 (a) Gi* Cluster map of Dengue incidence in 2020 (b) Significant map of Dengue incidence in 2020 (c) Gi* Cluster map of Dengue incidence in 2021 (d) Significant map of Dengue incidence in 2021 (e) Gi* Cluster map of Dengue incidence in 2022 (f) Significant map of Dengue incidence in 2022 (g) Gi* Cluster map of Dengue incidence in 2023 (h) Significant map of Dengue incidence in 2023

Exploring Population Density, Urbanization, and Night-Time Light (NTL) Impact using Gi* statistics

Table 2 illustrated a comparison of different clusters based on population density, urbanization, and NTL intensity for various regions in Nepal, categorized as either high or low. In terms of population density, areas like Rasuwa,

Table 2. **Gi cluster map of population density, urbanization and night time light (NTL) in 2020-2023**

Univariate analysis	Gi* statistics	
	High	**Low**
Population density	Rasuwa*	Mugu*
	Nuwakot**	Jumla*
	Kathmandu***	Humla*
	Lalitpur***	Dolpa*
	Makawanpur**	
	Dhading*	
	Kabhrepalanchok***	
	Bhaktapur***	
Urbanization	Rasuwa*	Mugu**
	Nuwakot**	Jumla*
	Kathmandu***	Humla**
	Lalitpur***	Dolpa*
	Makawanpur**	Kalikot*
	Dhading*	Dailekh*
	Kabhrepalanchok***	Rukum West*
	Bhaktapur**	Darchula*
		Baitadi*
		Bajhang**
		Bajura**
		Achham*
Night-time light 2020	Rasuwa*	Dolpa*
	Nuwakot**	Jumla*
	Kathmandu***	Jajarkot*
	Lalitpur***	Rukum West***
	Makawanpur**	Rukum East*
	Dhading*	Achham*
	Kabhrepalanchok***	Ramechhap*
	Bhaktapur**	Okhaldhunga*
	Sindhupalchok*	Khotang*
		Bhojpur**
		Solukhumbu**
		Sankhuwasabha**
		Taplejung*
Night-time light 2021	Rasuwa*	Achham*
	Nuwakot**	Jumla*
	Kathmandu***	Jajarkot*
	Lalitpur***	Rukum West***
	Makawanpur**	Rukum East*
	Kabhrepalanchok***	Ramechhap*
	Bhaktapur**	Okhaldhunga*
	Sindhupalchok*	Khotang**
		Bhojpur**
		Solukhumbu***
		Sankhuwasabha**
Night-time light 2022	Nuwakot**	Achham*
	Kathmandu***	Kalikot*
	Lalitpur**	Jumla**
	Makawanpur**	Jajarkot*
	Kabhrepalanchok***	Rukum West**
	Bhaktapur**	Rukum East*
	Sindhupalchok*	Dolpa*
	Solukhumbu**	Ramechhap*
		Khotang**
		Bhojpur**
		Sankhuwasabha**
		Taplejung*
Night-time light 2023	Nuwakot**	Jumla*
	Kathmandu**	Rukum West*
	Lalitpur***	Rukum East*
	Makawanpur**	Dolpa*
	Kabhrepalanchok***	Dolakha*
	Bhaktapur**	Okhaldhunga*
	Sindhupalchok*	Sankhuwasabha**
		Solukhumbu**
		Taplejung*

P-value 0.05*, 0.01**, 0.001***

Nuwakot, Kathmandu, Lalitpur, Makawanpur, Dhading, Kabhrepalanchok, and Bhaktapur were characterized by high density, with Kathmandu, Lalitpur, Kabhrepalanchok, and Bhaktapur standing out with the highest density levels. In contrast, regions such as Mugu, Jumla, Humla, and Dolpa were identified as low-density areas.

Similarly, for urbanization, regions such as Rasuwa, Nuwakot, Kathmandu, Lalitpur, Makawanpur, Dhading, Kabhrepalanchok, and Bhaktapur exhibit high levels of urban development, with Kathmandu, Lalitpur, Kabhrepalanchok, and Bhaktapur being highly urbanized. On the other hand, Mugu, Jumla, Humla, Dolpa, Kalikot, Dailekh, Rukum West, Darchula, Baitadi, Bajhang, Bajura, and Achham had lower levels of urbanization.

The NTL intensity, which served as a proxy for urban activity and development, showed that in 2020, regions like Rasuwa, Nuwakot, Kathmandu, Lalitpur, Makawanpur, Dhading, Kabhrepalanchok, Bhaktapur, and Sindhupalchok had high levels of light intensity. In contrast, areas such as Dolpa, Jumla, Jajarkot, Rukum West, Rukum East, Achham, Ramechhap, Okhaldhunga, Khotang, Bhojpur, Solukhumbu, Sankhuwasabha, and Taplejung had lower levels. This pattern of high and low light intensity continued in subsequent years, with Kathmandu, Lalitpur, Kabhrepalanchok, Bhaktapur, and Sindhupalchok consistently showing high light intensity from 2021 to 2023. Less urbanized regions like Rukum West, Rukum East, and Jumla fluctuated between high and low categories over the years.

In summary, regions with higher population density and urbanization, such as Kathmandu, Lalitpur, and Bhaktapur, consistently showed higher NTL intensity, indicating more developed infrastructure and urban activity. On the other hand, rural regions like Mugu, Jumla, and Dolpa consistently ranked low across all categories, highlighting regional disparities in development (Fig. 2).

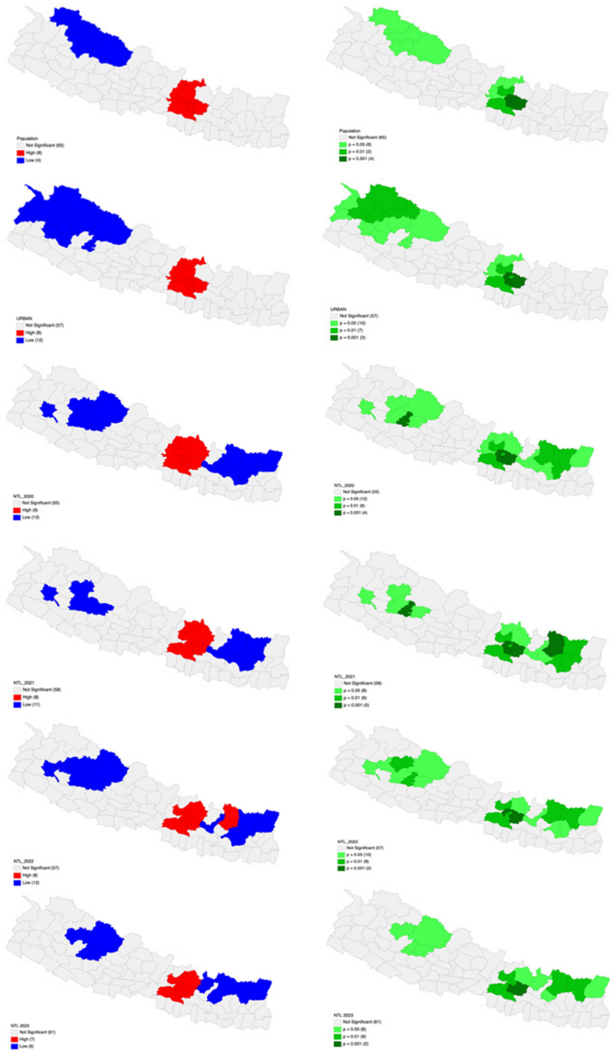

Figure 2. Gi* Cluster map of population density, urbanization and NTL in Nepal 2020-2023 (a) Univariate Gi* Cluster map of population density (b) Univariate Significant map of population density (c) Univariate Gi* Cluster map of urbanization (d) Univariate Significant map of urbanization (e) Univariate Gi* Cluster map of NTL in 2020 (f) Univariate Significant map of NTL in 2020 (g) Univariate Gi* Cluster map of NTL in 2021 (h) Univariate Significant map of NTL in 2021 (i) Univariate Gi* Cluster map of NTL in 2022 (j) Univariate Significant map of NTL in 2022 (k) Univariate Gi* Cluster map of NTL in 2023 (l) Univariate Significant map of NTL in 2023

Bivariate Analysis of District-Level Dengue Incidence and Ecology (2019-2023) Impact of Population Density on Dengue Fever Incidence

The bivariate LISA analysis revealed a statistically significant negative correlation between population density and the incidence of dengue in 2020, with Moran's I calculated at -0.083. Spatial analysis showed no areas where high population density coincided with high dengue incidence (Hot-spot or High-High clusters) in the surrounding three districts. Instead, LISA identified low population density and low dengue incidence clusters (Cold-spot or Low-Low clusters) in three districts: Mugu, Jumla, and Sindhupalchok.

In 2021, the bivariate LISA indicated a statistically significant negative correlation between population density and dengue incidence (Moran's I = -0.082). Consistent with the findings from 2020, no hot-spot clusters detected, however cold-spot clusters were found in Jumla and Rukum West districts.

The 2022 analysis demonstrated a shift in pattern, with a statistically significant positive correlation between population density and dengue incidence (Moran's I = 0.526). LISA analysis identified four hot-spot clusters in Kathmandu, Lalitpur, Bhaktapur, and Parsa, where high population density and dengue incidence were spatially clustered. Additionally, six cold-spot clusters were found in Bajura, Mugu, Jumla, Kalikot, Dang, and Salyan districts, indicating low population density and low dengue incidence.

In 2023, although the analysis yielded a Moran's I of -0.020, indicating no statistically significant spatial association between population density and dengue incidence (Table 3 and Fig. 3).

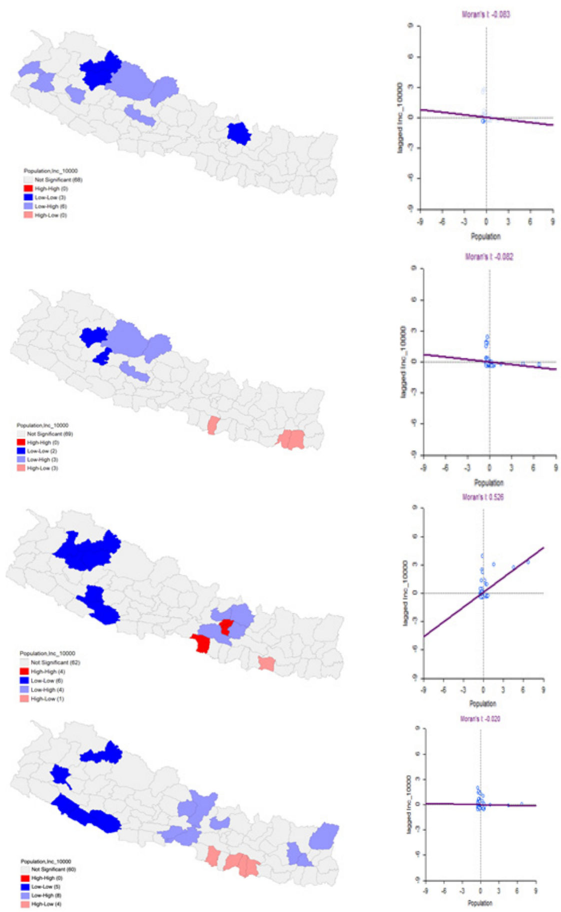

Figure 3. Bivariate analysis of population density and Dengue incidence in 2020-2023 (a) LISA map of population density with Dengue incidence in 2020 (b) Moran's I scatter plot of population density with Dengue incidence in 2020 (c) LISA map of population density with Dengue incidence in 2021 (d) Moran's I scatter plot of population density with Dengue incidence in 2021 (e) LISA map of population density with Dengue incidence in 2022 (f) Moran's, I scatter plot of population density with Dengue incidence in 2022 (g) LISA map of population density with Dengue incidence in 2023 (h) Moran's I scatter plot of population density with Dengue incidence in 2023

Table 3. Bivariate analysis of population density and Dengue incidence in 2020-2023

Year	Moran's I	LISA			
		HH	HL	LH	LL
2020	-0.083			Dolpa* Mustang* Baglung** Dailekh* Baitadi* Doti*	Mugu* Jumla* Sindhupalchok*
2021	-0.082		Rautahat* Sunsari* Morang*	Dolpa* Mustang* Baglung**	Jumla* Rukum West*
2022	0.526	Kathmandu*** Lalitpur*** Bhaktapur** Parsa*	Siraha*	Sindhupalchok* Nuwakot** Kabhrepalanchok*** Makawanpur***	Bajura* Mugu* Jumla* Kalikot* Dang* Salyan*
2023	-0.020		Bara* Sarlahi** Mahottari* Dhanusha*	Nawalpur* Chitawan* Gorkha* Lamjung* Nuwakot* Bhojpur* Dhankuta* Taplejung**	Achham* Mugu** Bardiya* Banke* Dang*

P-value 0.05*, 0.01**, 0.001***

Urbanization and Dengue Fever Incidence

The bivariate LISA analysis in 2020 revealed a statistically significant negative correlation between urbanization and dengue incidence, with Moran's I of -0.103. The analysis showed no significant High-High clusters, where urban areas and high dengue incidence coincided. While various patterns emerged, none met the criteria for significant hot-spot clusters. However, Low-Low clusters, where both urbanization and dengue incidence were low, were identified in Mugu, Jumla, and Sindhupalchok districts, extending into three neighbouring districts.

In 2021, the LISA analysis similarly revealed a negative correlation between urbanization and dengue incidence (Moran's I = -0.090). As in previous year, no High-High clusters were identified, indicating no significant concentration of urban areas and high dengue incidence. Low-Low clusters, where both urbanization and dengue were low, were observed in Jumla and Rukum West districts and their neighbouring areas.

In 2022, there was a spatial autocorrelation between urbanization and dengue incidence, reflected by a Moran's I of 0.458. The LISA analysis identified four High-High clusters in Kathmandu, Lalitpur, Bhaktapur, and Parsa, where high urbanization coincided with high dengue incidence, along with high values in the surrounding three districts. On the opposite end, six Low-Low clusters, indicating low urbanization and low dengue incidence, were found in Dang, Bajura, Mugu, Jumla, Kalikot, and Salyan districts.

By 2023, the Moran's I was 0.007, indicaing no statistically significant spatial pattern between urbanization and dengue incidence (Table 4 and Fig. 4).

Impact of Night-time light (NTL) Index on dengue incidence in Nepal

In 2020, the bivariate LISA analysis revealed a statistically significant negative correlation between NTL and dengue incidence, with Moran's I at -0.091. The analysis found no areas where high NTL coincided with high dengue incidence (High-High clusters). However, Low-Low clusters, where both nighttime light intensity and dengue incidence were low, were identified in Jumla, Mugu, and Sindhupalchok districts.

In 2021, a similar pattern was observed, showing a negative correlation between NTL and dengue incidence (Moran's I = -0.102). As in previous analysis, no High-High clusters were identified; however, two Low-Low clusters, where both nighttime NTL and dengue were low, were found in Jumla and Rukum West districts.

In 2022, a spatial autocorrelation between NTL and dengue incidence was detected, with a Moran's I of 0.415. The LISA analysis identified four High-High clusters, where NTL and high dengue incidence were concentrated in Kathmandu, Lalitpur, Bhaktapur, and Parsa districts, along with high values in the surrounding three districts. Conversely, six Low-Low clusters, indicating low nighttime light intensity and low dengue incidence, were found in Bajura, Mugu, Jumla, Kalikot, Salyan, and Dang districts. In 2023, the Moran's I was -0.068, but no statistically significant spatial pattern was observed between NTL and dengue incidence. (Table 5 and Fig. 5)

Table 4. Bivariate analysis of urbanization and Dengue incidence in 2020-2023

Years	Moran's I	LISA			
		HH	HL	LH	LL
2020	-0.103			Dolpa* Mustang* Baglung** Doti* Dailekh* Baitadi*	Mugu* Jumla* Sinduhupalchok*
2021	-0.090		Rautahat* Sunsari* Morang*	Dolpa* Mustang* Baglung**	Jumla* Rukum West*
2022	0.458	Kathmandu*** Lalitpur*** Bhaktapur** Parsa*	Siraha*	Sindhupalchok* Nuwakot** Kabhrepalanchok*** Makawanpur***	Dang* Bajura* Mugu* Jumla* Kalikot* Salyan*
2023	0.007	Chitawan*	Bara* Mahottari* Dhanusha* Sarlahi**	Gorkha* Nuwakot* Dhankuta* Bhojpur* Taplejung** Nawalpur* Lamjung*	Bardiya* Achham* Mugu** Banke* Dang*

P-value 0.05*, 0.01, 0.001*****

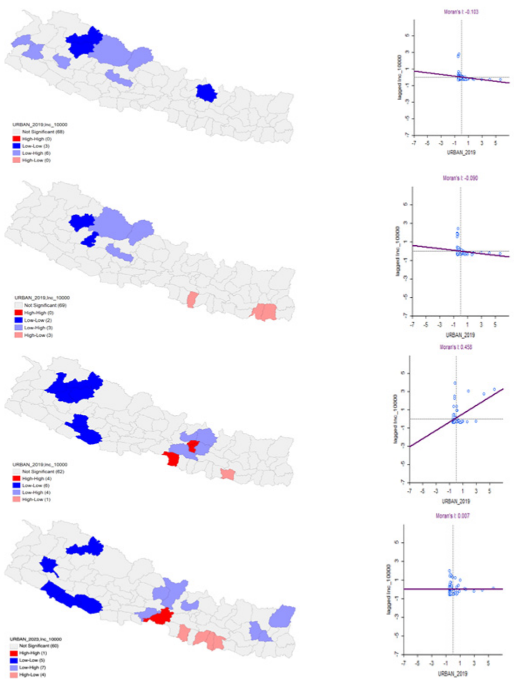

Figure 4. Bivariate analysis of urbanization and Dengue incidence in 2020-2023 (a) LISA map of urbanization with Dengue incidence in 2020 (b) Moran's I scatter plot of urbanization with Dengue incidence in 2020 (c) LISA map of urbanization with Dengue incidence in 2021 (d) Moran's I scatter plot of urbanization with Dengue incidence in 2021 (e) LISA map of urbanization with Dengue incidence in 2022 (f) Moran's I scatter plot of urbanization with Dengue incidence in 2022 (g) LISA map of urbanization with Dengue incidence in 2023 (h) Moran's I scatter plot of urbanization with Dengue incidence in 2023

DISCUSSION

In our setting, over the four years, dengue incidence varied significantly by district. High incidence was observed in different districts each year, reflecting the dynamic nature of dengue transmission. In 2020, areas like Baitadi and Doti had high incidence rates of dengue, which shifted to Dolpa and Mustang in 2021. In 2022, high incidence was seen in Parsa and Kathmandu, while in 2023, districts such as Taplejung and Dhankuta reported with high incidence rates. These changes emphasized the need for targeted public health interventions based on regional factors influencing dengue incidence.

The analysis of population density and dengue incidence over four years showed significant fluctuations. In 2020 and 2021, a negative correlation was found (Moran's I of -0.083 and -0.082), with cold-spot clusters in rural districts indicating low population density and dengue incidence. In 2022, the trend reversed, showing a positive correlation (Moran's I of 0.526) with hot-spot clusters in urban areas like Kathmandu, where high population density was linked to higher dengue incidence. By 2023, the correlation weakened (Moran's I of -0.020), suggesting that the relationship between population density and dengue incidence varies over time. These findings highlight the need for targeted interventions in high-density urban areas and continued focus on rural areas with low dengue incidence. Furthermore, our results are consistent with prior research, such as a study in Dhaka, Bangladesh, which observed similar correlations between urbanization and dengue transmission.[25] In Dhaka, most dengue cases occurred in areas with moderate to high population densities.[25] The risk of dengue was heightened in urban settings, particularly where stagnant water sources, like dirty ponds and drains, were prevalent. This underscored the role of urbanization and population density in influencing dengue transmission, emphasizing the importance of environmental conditions and settlement patterns in disease dynamics.[25] Another study conducted in Nepal, employing the Geographically Weighted Regression (GWR) model, emphasized that the average association of population density was moderately

Table 5. Bivariate analysis of Night time light (NTL) and Dengue incidence in 2020-2023

Years	Moran's I	LISA			
		HH	HL	LH	LL
2020	-0.091			Dolpa* Mustang* Doti* Dailekh* Baitadi* Baglung**	Mugu* Jumla* Sinduhu-palchok*
2021	-0.102		Rautahat* Sunsari* Morang*	Dolpa* Mustang* Baglung**	Jumla* Rukum West*
2022	0.415	Kathmandu*** Lalitpur*** Bhaktapur** Parsa*	Siraha*	Makawanpur*** Sindhupalchok* Nuwakot** Kabhrepalan chok***	Bajura* Mugu* Jumla* Kalikot* Salyan* Dang*
2023	-0.068	Chitawan*	Bara* Mahottari* Dhanusha* Sarlahi** Banke*	Gorkha* Nuwakot* Dhankuta* Bhojpur* Taplejung** Nawalpur* Lamjung*	Bardiya* Achham* Mugu** Dang*

P-value 0.05*, 0.01**, 0.001***

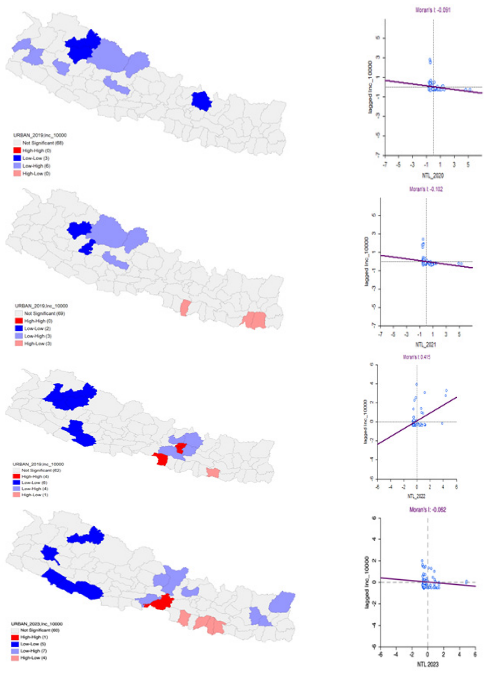

Figure 5. Bivariate analysis of nighttime light (NTL) and Dengue incidence in 2020-2023 (a) LISA map of NTL with Dengue incidence in 2020 (b) Moran's I scatter plot of NTL with Dengue incidence in 2020 (c) LISA map of NTL with Dengue incidence in 2021 (d) Moran's I scatter plot of NTL with Dengue incidence in 2021 (e) LISA map of NTL with Dengue incidence in 2022 (f) Moran's I scatter plot of NTL with Dengue incidence in 2022 (g) LISA map of NTL with Dengue incidence in 2023 (h) Moran's I scatter plot of NTL with Dengue incidence in 2023

positive (βpop density = 3.93).[26] However, the strength of this association varied significantly across different districts within Nepal.[26] Similarly, in China, using the same GWR model, researchers found that population size exerted strongly positive effects during epidemics, particularly notable in the boundary zones between Guangzhou City and Foshan City.[27]

In contrast, a study conducted in China using Maxent models projected that areas at high and moderate risk of Dengue Fever (DF) would expand significantly by 2070, with 48.47 million people, or 63.78% of the Pearl River Delta's population, residing in these high-risk zones.[28] This study identified a critical population density threshold of around 3,500 people per square kilometer, beyond which the risk of DF epidemics is expected to increase.[28] This study emphasized a specific population density threshold associated with increased risk, aligning with our observation that higher population density can be linked to higher dengue incidence in urban settings.[28] These findings underscored the localized variations in how population density and size influence epidemic dynamics in different geographical contexts, highlighting the need for targeted and context-specific interventions in disease management and prevention strategies.

The analysis of the relationship between urbanization and dengue incidence over four years revealed shifting spatial patterns. In 2020 and 2021, a negative correlation was observed, with no high-high clusters of high urbanization and dengue incidence; instead, low-low clusters were found in rural districts such as Mugu and Jumla, suggesting lower transmission in less urbanized areas. By 2022, the correlation shifted to positive (Moran's I = 0.458), identifying high-high clusters in urban centers like Kathmandu, where high urbanization was linked to increased dengue cases. In 2023, the correlation weakened, indicating variability over timeThese results emphasize the importance of implementing targeted public health interventions in urban settings while also acknowledging the mitigating benefits associated with reduced urbanization in rural areas.

Our study aligned with previous research, such as a study in Dhaka, Bangladesh, where dengue cases were predominantly in areas with moderate to high population densities.[25] The increased risk in urban environments, particularly where stagnant water sources like dirty ponds and drains were prevalent, highlighted the significant impact of urbanization and population density on dengue transmission, emphasizing the crucial role of environmental conditions and settlement patterns in disease dynamics.[25] In contrast, a study in China using Maxent models forecasted an increase in areas with high and moderate risk for Dengue Fever (DF) by 2070.[28] It predicted that 48.47 million people, or 63.78% of the population in the Pearl River Delta, will live in these high-risk zones. The study pinpointed a critical population density threshold of approximately 3,500 people per square kilometer, beyond which the risk of DF is anticipated to rise. This study emphasized a specific density threshold that influences DF risk, aligning with our observations that higher urbanization correlates with increased dengue incidence in urban settings.[28]

The analysis of NTL intensity and dengue incidence from 2020 to 2023 revealed shifting spatial patterns. In 2020 and 2021, there was a negative correlation, with no significant High-High clusters (high light intensity and high dengue incidence), but Low-Low clusters were found in rural districts like Jumla and Mugu, indicating lower urbanization and dengue transmission. In 2022, the correlation became positive, with high-high clusters identified in urban centers like Kathmandu, suggesting that urbanization and NTL activity increased dengue risk. However, by 2023, no significant spatial pattern was observed, underscoring the temporal fluctuations in this relationship. These findings emphasized the need for targeted interventions in urban areas while acknowledging the protective effects of rural settings with lower levels urbanization.

One of the key strengths of this study is its thorough examination of dengue incidence throughout all 77 districts of Nepal, which enables the recognition of areas needing focused dengue control efforts. Nevertheless, the study is constrained by its dependence on secondary data sources, preventing any assessment of causal relationships. Furthermore, being the secondary data the absence of real-time reporting, which could lead to under-reporting, over-reporting, or the misclassification of dengue cases.

CONCLUSION

The study revealed dynamic spatial patterns in dengue incidence across Nepal, influenced by socio-economic factors such as population density, urbanization, and NTL intensity. The shift from negative to positive correlations over the years indicates evolving patterns of dengue distribution, with urban and densely populated areas becoming more significant in recent years. The findings highlight the importance of targeted interventions based on detailed spatial and socio-economic analyses to effectively manage and control dengue outbreaks. Public health strategies should adapt to these changing patterns to reduce the burden of dengue in high-risk areas and improve overall health outcomes.

ACKNOWLEDGEMENTS

The authors are grateful to Mr. Rameshowar Parajuli from the Ministry of Health and Population in Nepal for their assistance with data processing and guidance during this study.

REFERENCES

1. Kularatne SA, Dalugama C. Dengue infection: Global importance, immunopathology and management. *Clin Med* (Lond). 2022 Jan;22(1):9-13. doi: 10.7861/clinmed.2021-0791. PMID: 35078789; PMCID: PMC8813012.
2. Dengue W. Guidelines for diagnosis, Treatment. Prevention and Control. 2009.
3. WHO. Dengue and severe dengue 2024 [Available from: https://www.who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue#:~:text=Dengue%20(break%2Dbone%20fever),aches%2C%20nausea%2C%20and%20rash.
4. Akinsulie OC, Idris I. Global re-emergence of dengue fever: The need for a rapid response and surveillance. *The Microbe.* 2024;4 doi: 10.1016/j.microb.2024.100107
5. Shepard DS, Undurraga EA, Halasa YA. Economic and disease burden of dengue in Southeast Asia. *PLoS Negl Trop Dis*. 2013;7(2):e2055. doi: 10.1371/journal.pntd.0002055. Epub 2013 Feb 21. PMID: 23437406; PMCID: PMC3578748.
6. WHO. Dengue - Nepal 2022 [Available from: https://www.who.int/emergencies/disease-outbreak-news/item/2022-DON412.
7. Chen S, Cao Z, Jiao L, Chen W, Prettner K, Kuhn M, et al. The global economic burden of dengue in 2020–2050: estimates and projections for 141 countries and territories. Available at SSRN 4691773. 2024.
8. Nepal EaDCD. Situation update of Dengue 2023, 2023.
9. IFRC. DREF OPERATION, 2023.
10. Shrestha SB, Pyakurel UR, Khanal M, Upadhyay M, Na-Bangchang K, Muhamad P, et al. Epidemiological situations and control strategies of vector-borne diseases in Nepal during 1998–2016. *J Health Res*. 2019;33(6):478-93.
11. Onen H, Luzala MM, Kigozi S, Sikumbili RM, Muanga CK, Zola EN, et al. Mosquito-Borne Diseases and Their Control Strategies: An Overview Focused on Green Synthesized Plant-Based Metallic Nanoparticles. *Insects.* 2023 Feb 23;14(3):221. doi: 10.3390/insects14030221. PMID: 36975906; PMCID: PMC10059804.
12. Nepal EaDCD. Prevention, Management and control of dengue in Nepal.pdf. 2019
13. Pakaya R, Daniel D, Widayani P. Spatial model of Dengue Hemorrhagic Fever (DHF) risk: scoping review. *BMC Public Health*. 2023;23(1):2448. doi: 10.1186/s12889-023-17185-3 [published Online First: 20231207]

14. Masrani AS, Nik Husain NR, Musa KI, Yasin AS. Trends and Spatial Pattern Analysis of Dengue Cases in Northeast Malaysia. *J Prev Med Public Health*. 2022 Jan;55(1):80-87. doi: 10.3961/jpmph.21.461. Epub 2022 Jan 6. PMID: 35135051; PMCID: PMC8841195.

15. Su Yin M, Bicout DJ, Haddawy P, Schöning J, Laosiritaworn Y, Sa-angchai P. Added-value of mosquito vector breeding sites from street view images in the risk mapping of dengue incidence in Thailand. *PLoS Negl Trop Dis*. 2021;15(3):e0009122.

16. Office NS. National Population and Housing Census 2021 (National Report), 2021.

17. Outlook N. Nepal: A Data Overview [Available from: https://nepaloutlook.com/nepal-overview/.

18. Nepal MoFA. Nepal Profile [Available from: https://mofa.gov.np/nepal-profile-updated/.

19. National Statistics Office (NSO) N. National Population and Housing Census 2021, 12th Population Census, 2021.

20. Division EaDC, Population MoHa, Nepal Go. Dengue Control Program [Available from: https://www.edcd.gov.np/.

21. Anselin L, Syabri I, Kho Y. GeoDa: an introduction to spatial data analysis. Handbook of applied spatial analysis: Software tools, methods and applications: Springer. 2009:73-89.

22. Getis A, Ord JK. The analysis of spatial association by use of distance statistics. Geographical analysis 1992;24(3):189-206.

23. Masrani AS, Nik Husain NR, Musa KI, Yasin AS. Trends and Spatial Pattern Analysis of Dengue Cases in Northeast Malaysia. *J Prev Med Public Health*. 2022 Jan;55(1):80-87.

24. Anselin L. Local indicators of spatial association—LISA. *Geographical analysis.* 1995;27(2):93-115.

25. Kamal ASMM, Al-Montakim MN, Hasan MA, Mitu MMP, Gazi MY, Uddin MM, et al. Relationship between Urban Environmental Components and Dengue Prevalence in Dhaka City-An Approach of Spatial Analysis of Satellite Remote Sensing, Hydro-Climatic, and Census Dengue Data. *Int J Environ Res Public Health*. 2023 Feb 21;20(5):3858.

26. Acharya BK, Cao C, Lakes T, Chen W, Naeem S, Pandit S. Modeling the spatially varying risk factors of dengue fever in Jhapa district, Nepal, using the semi-parametric geographically weighted regression model. *Int J Biometeorol*. 2018 Nov;62(11):1973-86.

27. Ren H, Zheng L, Li Q, Yuan W, Lu L. Exploring Determinants of Spatial Variations in the Dengue Fever Epidemic Using Geographically Weighted Regression Model: A Case Study in the Joint Guangzhou-Foshan Area, China, 2014. *Int J Environ Res Public Health.* 2017 Dec 6;14(12):1518.

28. Wu W, Ren H, Lu L. Increasingly expanded future risk of dengue fever in the Pearl River Delta, China. *PLoS Negl Trop Dis.* 2021 Sep 24;15(9):e0009745.