RESEARCH PAPER

DETERMINANTS AND SPATIAL DISTRIBUTION OF DENGUE FEVER OUTBREAKS IN URBAN PAKISTAN: A GIS-BASED CROSS-SECTIONAL STUDY

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ABSTRACT

OBJECTIVE: To determine the socio-environmental factors and describe the spatial distribution patterns of dengue fever outbreaks in the big cities of Pakistan through the use of geospatial analytical methods.

MATERIAL AND METHODS: Cross-sectional study using GIS was performed with the use of geocoded, laboratory tested dengue case data (n=148,762) across five metropolitan cities (Karachi, Lahore, Islamabad/Rawalpindi, Peshawar, Faisalabad) within the period of 2019-2023. The definition of the spatial units was on the Union Council (UC) level (n=1,847). The satellite images and meteorological stations together with the national census data were incorporated as environmental, climatic, demographic, and urban infrastructure variables. The Geographically Weighted Regression (GWR) and spatial lag models have found the important predictors of dengue incidences. The level of statistical significance was $p < 0.05$.

RESULTS: There were high levels of spatial clustering of dengue cases in all the five cities (Global Moran's I = 0.412, $p < 0.001$). An association was found between high-incidence UCs and high mean monthly temperatures (IRR = 1.38, $p < 0.001$), great variation of precipitation (IRR = 1.24, $p = 0.003$), dense informal settlement cover (IRR = 1.52, $p < 0.001$), and ineffective solid waste management. The spatial regression model was significant in terms of variance (Adjusted $R^2 = 0.784$) and spatial dependency ($p < 0.001$).

CONCLUSION: Dengue fever in urban Pakistan demonstrates a high level of spatial heterogeneity caused by the synergistic relationships between the variability of climatic conditions, unplanned rapid urbanization, and infrastructure deficiencies. To reduce the intensity of the outbreak and focus resources to the maximum, geographically stratified intervention for vector control and high-resolution spatial surveillance systems are necessary.

KEYWORDS: Dengue fever, spatial epidemiology, GIS, vector-borne disease.

How to cite this article: Masood R, Asghar A, Javed R, Saddique A, Ahmed HR, Adil T. Determinants and Spatial Distribution of Dengue Fever Outbreaks in Urban Pakistan: A GIS-Based Cross-Sectional Study. Int J Drug Deliv Technol. 2026;16(5): 1351-1357. DOI: 10.25258/ijddt.16.5.125

Source of support: Nil.

Conflict of interest: None

INTRODUCTION

Dengue fever is among the fastest-growing arboviral diseases worldwide as it is estimated there is 390 million cases of the disease each year in over 125 countries.[1] The disease is a significant burden to the endemic areas due to its high morbidity, the health care burden, and economic impact caused by four different serotypes of dengue virus (DENV-1 to DENV-4) and is mainly carried by Aedesaegypti and to a smaller extent,Aedesalbopictus mosquitoes.[2]The epidemiological situation has changed radically over the past few years, and sometimes the number of cases is more than 100,000 per year and mortality rates during monsoon and post-monsoon seasons are very high.[3]

The environmental, climatic, socioeconomic and the urban morphological factors interact in a complex manner and strongly affect the ecological and epidemiological dynamics of dengue. The extrinsic incubation period of the virus in the mosquito is directly regulated by temperature, and optimum transmission of the virus takes place at 24o C-32o C; above that the viral replication and insect survival decreases.[4] The availability and permanency of artificial and natural breeding locations, such as discarded containers, water storage tanks, blocked drains, and construction debris is controlled by rainfall and humidity.[5] These climatic drivers in South Asian urbanizing landscape environments are overlapped with anthropogenic landscape alterations, resulting in heterogeneous micro habitats, which are conducive to Aedes population growth.[6] The urban centers in Pakistan have been facing a rate of population growth of over 3 percent in a year with uncontrolled population growth, proliferation of informal settlements, and disintegrated municipal services.[7] The lack of solid waste management and irregular water supply, as well as the poor drainage systems, all contribute to the maintenance of peridomestic vectors habitats, which is why residential areas become constant areas of transmission.[8] Moreover, socioeconomic inequalities also have effects on the quality of housing, the availability of healthcare, and the awareness of the community, which mediate the exposure risk and the effectiveness of case reporting.[9]The available literature on dengue in Pakistan has concentrated on the temporal trends, serological surveillance, and clinical management to a greater extent and there is little inclusion of high-resolution geospatial analytics at the sub-district level.[10] A number of studies have reported relationships between rainfall, temperature and dengue rates based on time-series models but none of them have considered spatial non-stationarity, socioeconomic gradients by neighborhood and urban land-use fragmentation.[11] Additionally, the fast growth of peri-urban belts, informal settlements which are prone to floods and climate-related hydrological changes in such cities as Karachi and Lahore have significantly changed the ecology of vectors and required new spatial risk evaluation.[12] The lack of geospatial databases, which are not standardized and are not found in more than one city, has also been another obstacle to comparative analysis and the construction of nationally applicable early warning systems.[13] The latest developments of open-source GIS platforms, machine learning-based spatial regression, and high-resolution remote sensors products currently offer unprecedented possibilities to overcome these gaps[14]. Through aggregation of the level of the Union Council, multi-source environmental data and powerful spatial statistical methods, the current studies can shift to predictive rather than descriptive epidemiology based on action.[15]

This study presents a scalable dengue surveillance framework by combining high-resolution epidemiological data with multi-layered geospatial analytics, which is consistent with the aims of the National Dengue Control Program in Pakistan and other mitigation strategies against arboviral diseases in the world. In a world where climate change is a reality and urban change is accelerating and entailing the need to rethink healthcare provision, spatially informed epidemiology is not only an analytical device, but it is a health need of the population. The understanding of the location and the reasons of the dengue clusters development is the cornerstone of providing the precise, fair and sustainable measures to protect the vulnerable populations in the cities.

MATERIAL AND METHODS

The study adopted the cross-sectional study design that is GIS based to determine the spatial pattern and socio-environmental factors of dengue fever outbreaks in five major metropolitan Karachi, Lahore, Islamabad/Rawalpindi twin cities, Peshawar and Faisalabad in Pakistan. The cities have been chosen according to their past history of dengue infection, bulk of the population of over 1000 people per square kilometer, and recorded the urban growth patterns, and accessibility to geocoded epidemiological data. The analysis of the study was between January 2019 and December 2023 covering several transmission seasons, the severe 2022 post-flood epidemic, thus providing strong coverage of the climatic and epidemiological variability.Sources of Data and Construction of Variables.The provincial health departments provided the data on dengue cases that were cross-validated with the records of National Institute of Health (NIH) Islamabad laboratories confirmation. The cases were characterized as clinically suspected dengue which had a positive NS1 antigen, IgM ELISA or RT-PCR results. Hospital admission records and community health worker reports and GIS enabled mobile reporting platforms were used to geocode all cases to their residential UC. There were unique patient identifiers and spatial deduplication algorithms with the help of which duplicate entries and cross-district referrals were excluded. There were many authoritative databases where the environmental and climatic variables were obtained. Temperature and precipitation data were obtained on the ground stations of the Pakistan

Meteorological Department (PMD) on a daily basis and bias-corrected with the CHIRPS v2.0 satellite rainfall estimates at a 5 km resolution. ERA5-Land reanalysis data was used to obtain relative humidity. The temperature of the land surface (LST) and Normalized Difference Vegetation Index (NDVI) were obtained at 1 km spatial resolution in the 8-day MODIS Terra/Aqua composite products (MOD11A2 and MOD13Q1). The variables of urban morphology, such as built-up area fraction, road network density, and impervious surface coverage, were digitized with the help of the Sentinel-2 MSI images (10 m resolution) with the object-based image classification in QGIS. The OpenStreetMap (OSM) annotations of the informal settlement boundaries were checked against the high-resolution WorldView-3 imagery and municipality master plans. Primary spatial pattern analysis was carried out by using the Global Moran I that was used to determine the total spatial autocorrelation of dengue incidence within the study area. The local spatial clustering was measured based on the Local Indicators of Spatial Association (LISA) by Anselin and the analysis of the hot spot and cold spot (Getis-OrdGi) to determine statistically significant high-high (hotspots) and low-low (coldspots) clusters. Continuous risk surfaces were produced by Kernel Density Estimation (KDE) with an adaptive bandwidth of 1.5 km which made it easy to visualize the transmission intensity gradients. Boundary effects and spatial outliers were fixed with queen contiguity weight matrices and using row-standardization. The incidence of dengue was determined as cases of dengue which were confirmed by laboratories per 10,000 population in the UC level. Descriptive statistics were used to describe the distribution of cases, demographics and the environmental conditions. The spatial correlations between two variables were calculated with the help of the rank coefficient of Spearman with spatial weights. A spatial Poisson regression model was used in multivariable analysis in order to explain overdispersion of count data and space dependency. The model specification in the end was fixed effects of climatic variables (mean temperature, cumulative rainfall, humidity), urban infrastructure (informal settlement coverage, waste management score, drainage quality index, population density), socioeconomic variables (literacy rate, sanitation access, income deprivation index) and healthcare access measures. The association between temperature and rainfall as well as informal settlement density and waste management were experimented to produce the synergistic ecological drivers. Information that was validated was through cross-referencing of hospital data with community surveillance records, spatial assessment by ground-truting 5 percent of randomly selected UC centroid with GPS positions and time verification by comparison with past outbreak data. Missing data (Less than 8% by variables) were interpolated using spatial k-nearest neighbor interpolation. The Institutional Review Board of the Pakistan Medical Research Council (PMRC/IRB/2023/084) gave the ethical approval. All the patient identifiers were coded, and spatial coordinates were coaggregated to UC boundaries to eliminate individual re-identification. The research was in line with the principles of epidemiological research as upheld in the Declaration of Helsinki and in accordance with the national data protection regulations.

RESULTS

The spatial autocorrelation analysis determined high degree of clustering (Global Moran I = 0.412, $p = 0.001$) which means that dengue incidence is not spread randomly but it can be found in some geographic enclaves. The following tables show statistically significant relationships ($p < 0.05$) between the dengue occurrence and the major socio-environmental determinants, the spatial clustering measures, and the multivariate spatial regression results, with the description of the interpretations provided below each table.

Table 1 shows that the burden of dengue is significantly (statistically significant) affected by socioeconomic gradient. The high income inequality ($p = 0.002$) is the importance of the economic deprivation to access to vector-proof housing, access to clean water, and access to personal healthcare that increases the exposure risk and the delay in reporting the cases.

Table 1: The Socioeconomic and Demographic Characteristics according to Dengue Burden category

Variable	High-Burden UCs (n=412)	Low-Burden UCs (n=1,435)	p-value
Mean Population Density (per km^2)	28,450 ± 6,310	14,220 ± 5,890	<0.001
Informal Settlement Coverage (%)	34.7 ± 8.2	12.1 ± 4.5	<0.001
Literacy Rate (%)	58.3 ± 9.1	71.6 ± 6.8	<0.001

Variable	High-Burden UCs (n=412)	Low-Burden UCs (n=1,435)	p-value
Sanitation Access (%)	62.4 ± 7.3	84.9 ± 5.2	<0.001

Table 2 demonstrates that high thermal and hydrological factors are highly associated with incidence of dengue. UCs with high burden have a much higher temperature and monsoon rainfall, which offer the best conditions that Aedes larvae can develop as well as the virus to multiply. The statistically significant relationships (all $p < 0.005$) affirm that microclimatic changes caused by the urban heat island processes and hydrological changes are important environmental enhancers of the dengue disease.

Table 2: Climatic and Environmental Determinants of Dengue Incidence.

Environmental Variable	High-Burden UCs	[illegible]	[illegible]
Mean Annual Temperature (°C)	27.8 ± 1.4	[illegible]	[illegible]
Monsoon Season Rainfall (mm)	384 ± 62	[illegible]	[illegible]
Mean Relative Humidity (%)	68.4 ± 5.1	[illegible]	[illegible]
NDVI (Vegetation Index)	0.21 ± 0.06	[illegible]	[illegible]
Land Surface Temperature (°C)	34.2 ± 2.8	30.6 ± 2.1	0.004

Table 3 demonstrates that high-transmission UCs have important infrastructural shortcomings. The poor collection of waste provides high breeding areas in empty containers and biotic wastes. The significance of the differences between the variables is high ($p < 0.005$) to prove the fact that municipal service fragmentation and poor urban planning are the root causes of dengue spatial clustering.

Table 3: Municipal Service and Urban infrastructure.

Infrastructure Metric	High-Burden UCs	Low-Burden UCs	p-value
Solid Waste Collection Frequency (days/week)	2.1 ± 0.8	4.6 ± 1.1	<0.001
Drainage Coverage (% of UC area)	41.3 ± 9.2	76.8 ± 6.5	<0.001
Open Drain Length (km/10 km²)	3.8 ± 1.2	1.1 ± 0.4	0.001
Water Storage Tank Prevalence (%)	89.4 ± 5.6	52.7 ± 7.3	<0.001
Healthcare Facility Density	1.8 ± 0.5	3.4 ± 0.7	0.003

Table 4 validates strong spatial clustering in all the metropolis centers with Global Moran I values of 0.329 to 0.451 (all $p < 0.001$). These findings confirm the non-random, structurally laid out, nature of dengue transmission and also prove the effectiveness of spatial statistics in prioritizing intervention areas.

Table 4: Results of the Spatial Autocorrelation and the Hotspot Analysis

City	Global Moran's I	p-value	Significant Hotspot UCs (%)	Gi Max Z-Score	KDE Peak Incidence (per 10k)
Karachi	0.387	<0.001	24.1	4.82	142.6
Lahore	0.451	<0.001	28.7	5.13	168.4
Islamabad/Rawalpindi	0.329	<0.001	19.3	3.97	98.2
Peshawar	0.402	<0.001	26.5	4.56	131.8
Faisalabad	0.438	<0.001	30.2	5.01	156.3

Table 5 shows the final spatial regression model, and it explains 78.4% of the variance in the dengue incidence. All of the major predictors have a statistical significance ($p < 0.005$). Such spatial dependence is such that multi-UC intervention strategies are required, instead of the independent actions of municipalities.

Table 5: The output of Multivariate Spatial Poisson Regression Model.

Predictor Variable	Incidence Rate Ratio (IRR)	95% CI	p-value
Mean Temperature (per 1°C ↑)	1.38	1.29 – 1.47	<0.001

Predictor Variable	Incidence Rate Ratio (IRR)	95% CI	p-value
Monsoon Rainfall (per 10mm ↑)	1.24	1.09 – 1.41	0.003
Informal Settlement Coverage (%)	1.52	1.38 – 1.67	<0.001
Solid Waste Collection Frequency	0.81	0.73 – 0.90	0.001
Sanitation Access (%)	0.79	0.68 – 0.92	0.004
Spatial Lag Term (ρ)	0.316	0.241 – 0.391	<0.001
Adjusted R² / AIC	0.784 / 4,812	—	—

DISCUSSION

The results of this cross-sectional study based on GIS give strong arguments that outbreaks of dengue fever in urban Pakistan are structured spatially, ecologically and deeply embedded in inequities in urban infrastructure. Through the combination of high-resolution epidemiology and multi-layered geospatial analytics, we will show that dengue transmission represents not a random urban occurrence but a foreseeable outcome of both climatic and environmental and socioeconomic factors. These findings are consistent with current literature on the spatial epidemiology, but provide new and Pakistan-specific information on the microscale mechanisms of arboviral disease clustering.[16]

Climatic variables also became the main factors in the occurrence of dengue, temperature and monsoon rainfall showed a significant positive relationship. The IRR of 1.38 per 1 o C rise is consistent with the biomechanical assumptions of dengue by transmissions that hot temperatures will hasten mosquito growth and development, decrease the extrinsic incubation duration, and raise biteming frequency.[17] The variability of rainfall, which is intense and sporadic monsoon rainfall, forms temporary water containers and floods poorly drained areas, which are the best oviposition environments.[18]

Deficits in urban morphology and infrastructures were also equally vital factors with informal settlement cover, inefficient waste disposal, and the lack of access to sanitation being good predictors of high-burden regions. The 52 percent risk increment with the informal settlement density is a measure of the combination of the substandard housing, intermittent water supply, and dependence on uncovered storage tanks that all contribute to the continuation of the entire yearly populations of vectors.[19] City fragmentation of services, especially uneven solid waste collection and open drainage systems, provides a stable ecological niche in the development of Aedes. The results are consistent with the body of urban health geography literature that highlights the fact that the characteristics of urban poor- and middle-income countries as places of urban inequality are central to the manifestations of the various diseases they transmit.[20] The safeguarding impact of the enhanced sanitation and the density of healthcare facilities are additional indicators of the significance of the integrated urban growth and the access to primary care in the reduction of dengue burden.[21] The reactive larviciding or the fogging campaigns will not be epidemiologically adequate and will not be economically feasible without paying attention to these structural determinants.

Conventional reporting mechanisms where UCs are viewed as autonomous entities overlook cross-jurisdictional transmission processes and slow down the process of co-ordinating responses. The relations established by Geographically Weighted Regression supported the non-stationary relationships, according to which, the strength of the determinant-outcome associations varied across the locations. As an example, negative impacts of temperature were magnified in the north peri-urban areas, whereas the lack of infrastructure prevailed in the transmission drivers in the southern informal areas. This geographical dissimilarity requires the local intervention models instead of homogenous application of the policies.[22] Public health infrastructure The recent experiences of implementing GIS-based early warning systems in Colombia and Vietnam have shown that the addition of spatial lag terms and dynamic risk surfaces increases the accuracy of predicting an outbreak by 3540 that provides the feasibility of the pathway to be followed by the Pakistani public health infrastructure.[23]

It has a number of limitations that should be mentioned. First, the cross-sectional design does not allow causal inference and does not even allow the temporal lags between environmental exposure and manifestation of the cases. Politically, this research paper can offer practical evidence on how to reorganize the dengue control system in Pakistan. In addition, undertaking spatial epidemiology and GIS analytics training to the public health officers will increase the capacity to make decisions based on data. Spatial risk stratification should be embraced by the National Dengue Control Program in order to maximize budget allocation such that scarce resources will be distributed to areas where the epidemiological impact will be the greatest. The technology transfer and capacity building can be further achieved through international partnership with GIS research networks.

Dengue fever in urban Pakistan is a socio-environmentally-based, spatially-centered, public health problem requiring exact epidemiology as opposed to blanket-interventions. Climatic variability, unplanned urbanization and neglect of infrastructures have converged to establish permanent enclaves of transmission that marginalized communities are overburdened. With the help of GIS, spatial statistics, and multi-layered determinant analysis, the paper offers a scalable evidence-based model of focused control of vectors, city planning reform, and development of early warning systems. With the increasing rate of climatic change and the increasing population in cities, incorporating spatial intelligence in the strategy of population health is no longer a choice of action; it is needed to protect the urban population and ensure sustainable dengue control in Pakistan and other dengue-endemic countries.

CONCLUSION

Although urban Pakistan outbreaks of dengue fever are highly space clustered, they are largely influenced by synergistic interplay of high temperatures, monsoon rain, growth of informal settlement, poor waste disposal and lack of access to sanitation. Spatial analysis Spatial analysis using GIS validates that the distribution of the transmission hotspots is not random, but rather, is clustered in peri-urban and infrastructurally marginalized Union Councils and has a high level of spillover effects at the neighborhood level. The future of longitudinal and predictive spatial modelling will enhance the ability to improve the early warning systems and resource distribution towards a sustainable management of arboviral diseases in the fast growing endemic areas.

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