DETERMINATION OF SPATIO-TEMPORAL TRANSMISSION PATTERNS OF DENGUE USING INDIVIDUAL PATIENT DYNAMICS: A CASE STUDY OF NCT DELHI

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ABSTRACT

Understanding the spatio-temporal transmission patterns of infectious disease is crucial for effective policymaking and containment strategies. Traditional approaches to study disease transmission often overlook localized patterns due to reliance on aggregate data and broad geographical scales. In contrast, this study focuses on individual patient data, allowing for a more granular analysis. By integrating patient records and hospital trip data, this study provides a comprehensive visualisation of the transmission process. This study aims to determine spatio-temporal patterns of dengue by utilizing individual patient data and their hospital trips to analyse dengue transmission in NCT Delhi during 2015-2022. Geospatial techniques have been employed to identify key mobility patterns associated with dengue transmission. Here Dengue Disease Monitoring (DDM) framework has been used to understand the spread of dengue through patient mobility in NCT Delhi. The study provides information regarding spatio-temporal dynamics of transmission so that effective resource allocation may be provided in order to implement targeted interventions in high-risk areas. It has been found that the incidence is very high in the central region of NCT Delhi. About 46.6% have been reported to nearby hospitals designated to dengue. On an average, it has been observed that patients tend to prefer travelling 7.5 km for treatment of dengue. Overall during 2015-2022, more frequent clusters have been formed in New Delhi District. Based on this study the movement of patients have a significant effect on dengue transmission. It is suggested to improve healthcare in vulnerable regions by offering specialized dengue treatment and increasing the number of designated hospitals specifically for dengue cases. The findings will help in formulating evidence-based policies to limit the spread of dengue, thus improving public health outcomes and reducing the burden of the dengue on affected communities.

1. INTRODUCTION

Dengue is a major global health concern, particularly in highly populated urban areas of tropical and subtropical regions, where human mobility are high (WHO, 2021). The disease is transmitted through the bite of infected Aedes mosquitoes, predominantly Aedes aegypti, with symptoms ranging from mild flu-like to severe manifestations. There are three modes of dengue transmission i.e. mosquito to human, human to mosquito and infected mother to child (CDC, 2023). Thus, the transmission of dengue typically occurs through the interaction between mosquitoes and humans. In order to develop effective strategies for controlling and preventing dengue, it is crucial to have a thorough understanding of the spatiotemporal dynamics of its transmission.

The study regarding movement of infected individuals is crucial to analyse the relationship between human mobility and dengue transmission patterns (Enduri and Jolad, 2018). It is widely recognized that there is a positive correlation between dengue transmission and human mobility, determining precise spatio-temporal patterns of transmission has been a complex task (Chen et al., 2019). Traditional approaches to studying disease transmission have often relied on aggregate data or broad geographical scales, which may overlook localized dynamics and hinder the identification of transmission hotspots (Grubaugh et al., 2019). These approaches provide limited insights into the individual-level dynamics that contribute to the overall spread of the disease.

Human mobility itself is a complex phenomenon. People move within and between different regions, communities, and even countries, often driven by factors such as work, tourism, social interactions, and population movements. Understanding and capturing the intricacies of human mobility patterns and their relationship to dengue transmission is a challenging task that requires comprehensive data collection, sophisticated analytical methods, and robust modelling approaches. Efforts to determine the spatiotemporal patterns of dengue transmission involve the use of various data sources, including epidemiological data, travel records, population movement data, and environmental variables. Various studies made an effort to study disease dynamics using different data like mobile usage (Liebig et al., 2021), road network (Chen et al., 2019; Mahabir et al., 2012).

The role of hospitals as a potential medium for disease transmission, including dengue, have not been extensively explored. In healthcare systems, there is a possibility of nosocomial infections, i.e. infections acquired during hospital stays or healthcare interactions. However, the potential for hospital-acquired infections (HAI), including dengue, emphasises the significance of maintaining appropriate infection control measures within healthcare facilities. Research studying HAI related to food-borne (Bisht et al., 2021), blood-borne (Alshahrani et al., 2021; Wicker et al., 2008) and airborne (Eames et al., 2009) have been studied. However, such studies for vector-borne disease, including those transmitted by mosquitoes such as dengue, have not been studied.

Understanding the potential for vector-borne diseases to be acquired or transmitted within healthcare facilities is essential for patient safety and infection control practices. Thus, to overcome the limitation, this study utilizes a novel framework called Dengue Disease Monitoring framework (DDM) (Sharma et al., 2023) for determining the spread and transmission. This framework utilizes individual patient data and their hospital trips to determine the spatiotemporal transmission patterns of dengue using geospatial techniques. By incorporating individual patient data, the DDM framework allows for a more granular and comprehensive examination of disease transmission within hospital settings.

The utilization of geospatial techniques further enhances the analysis by providing spatial context and identifying potential

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hotspots or clusters of dengue transmission within and around healthcare facilities. By examining the movements and interactions of infected individuals, patterns of transmission, and high-risk areas may be identified. Further, the transmission timing may guide resource allocation and the implementation of targeted interventions, such as vector control measures and public awareness campaigns. By improving the ability to identify and respond to dengue transmission patterns, effective control and prevention strategies may be initiated, ultimately reducing the burden of dengue on affected communities and improving public health outcomes.

2. DATA AND METHODS

2.1 Dataset used

A descriptive retrospective study has been conducted using routinely collected dengue surveillance data during 2015-2022. The primary data used for this study consists of individual patient records and hospital trip data. This data has been collected from Municipal Corporation Delhi and have been compiled using GIS as shown in Fig 1.

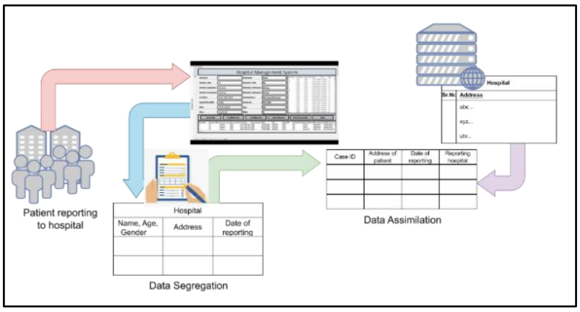

Fig 1. Process of data collection and database creation

The data consists of daily hospitalised and laboratory confirmed dengue cases in Delhi during 2015-2022. The list includes address of the patient, hospital where the case was registered along with the date of reporting. For this study, only cases that have been reported to sentinel surveillance hospitals for vector-borne disease surveillance are considered. The administrative shapefiles of NCT Delhi has been downloaded from website of Survey of India (SOI, 2023). Population data for each ward in Delhi was taken from Census of India 2011 (Census, 2011) along with Sample Registration System (SRS) statistical report for each year during study period. The base population in the year 2011 projected for annual population determination during the study period using the cohort component method. The general equation is:

$$Pt = Pt\text{-}1 + Bt - Dt + It \tag{1}$$

Where: Pt = population at time t, Pt-1 = population at time t-1 (previous year), Bt = number of births in year t, Dt = number of deaths in year t, It = net migration in year t (immigration minus emigration)

2.2 Study Area

The study area for this research is NCT Delhi with central coordinates of 28° 40' 45" N and 77° 4' 11" E (Fig 2). It is divided into multiple administrative districts, each with its distinct characteristics and population densities. Major land use classes consist of residential areas, commercial and industrial zones, green spaces, transportation infrastructure, and water bodies. The city has a subtropical climate, with a monsoon season from July to September. The city faces periodic flood-like conditions during this period due to inadequate drainage systems, resulting in waterlogging and inundation in low-lying areas, creating favourable conditions for Aedes mosquitoes to grow (Telle et al., 2021). At present, NCT Delhi has 280 governments and 52 private hospitals and large number of private clinics. Out of 805 sentinel surveillance hospitals for vector borne disease surveillance in India, 35 are situated in NCT Delhi (Fig 2) (NVBDCP, 2023).

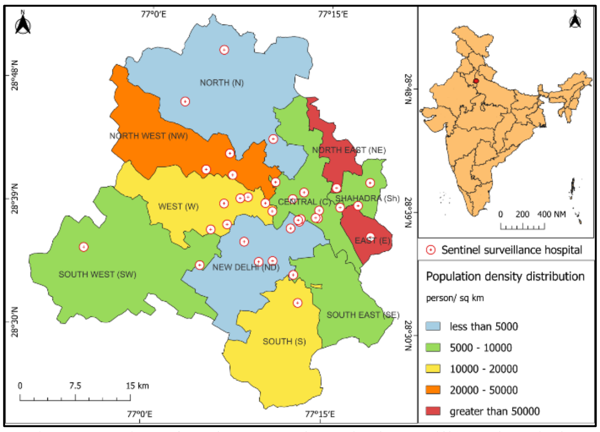

Fig 2. Location of study area and Sentinel surveillance hospitals

3. METHODOLOGY

The research integrates various data sources, including temporal patient records and hospital trip data to construct a comprehensive picture of dengue transmission in NCT Delhi. The overall methodology incorporates DDM framework module 1 (Sharma et al., 2023). The flowchart of methodology followed is shown in Fig 3. The collected data requires pre-processing to ensure data quality and compatibility for spatial analysis. This involves cleaning the data, resolving inconsistencies, and standardizing the data format. Patient records and hospital data are linked based on unique identifiers i.e. Hospital, enabling the association of temporal movement of patient with their respective infection locations.

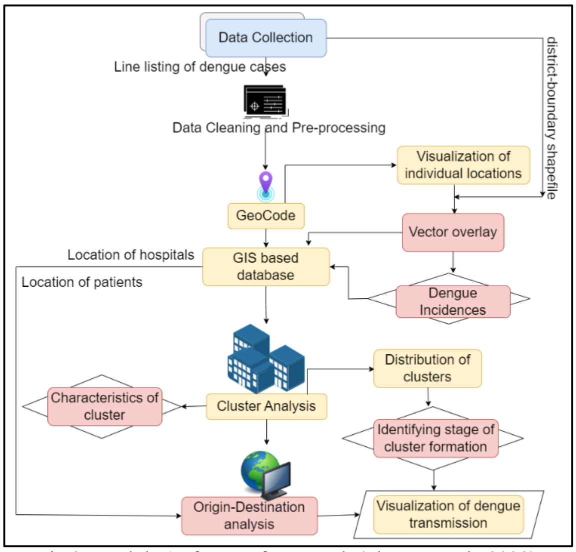

Fig 3. Module 1 of DDM framework (Sharma et al., 2023)

First of all, each address has been assigned a pin code, enabling the identification of their respective localities. Google Earth has been used to geocode both patient and hospital locations. Using the case ID as a key, the two geocoded files have been linked together for further analysis. After geocoding, by overlaying the raw patient location data onto the district boundaries of Delhi dengue incidences have been determined. Incidence of dengue has been calculated as cases reported in district per total population in thousands (Chaikaew et al., 2009).

Space-time based clusters have been identified using Kulldorff Spatial Scan Statistic (Kulldorff, 1997). The discrete Poisson probability model has been used for identifying spatio-temporal clusters (Alemu et al., 2013). For each year, spatio-temporal clusters have been identified at a time precision of 7 days (Machault et al., 2014). For identifying a cluster, a condition of “No Cluster Centroids in Other Clusters” has been selected to visualize the movement in the cluster center. The output of spatio-temporal scan is sensitive to various parameters, like the minimum size of spatial and temporal cluster.

In order to select optimal parameters, 2021 has been analysed using varying spatial window from 5% to 50% of population at risk by increments of 1%. Similarly, temporal window has been selected by testing sizes from 10% to 50% of study period by increments of 1%. Based on the optimal spatio-temporal parameters to capture the dynamic trend (spatial as 10% of population and temporal at 50% of the survey period), retrospective space-time scanning analysis has been carried out to identify areas and time periods of potential clusters with significantly dengue incidences than that of nearby areas during entire study period. The P-values as < 0.05 of Log Likelihood Ratio (LLR) has been estimated with 9999 Monte Carlo simulations. A p-value <0.05 indicates a significantly high risk of dengue inside of the scan window.

The Origin-Destination (OD) analysis has been performed on QGIS Desktop version 3.22.15. OD matrix has been constructed to determine the distance between the location of patient and hospital where case is reported. It also helps to identify the connectivity between different locations or entities involved in the transmission process. Thus, it helps visualize the movement of patients and their preferences for specific hospitals for treatment. Further, it has been compared to identified spatio-temporal clusters to study the impact of patient movement on dengue transmission.

4. RESULTS & DISCUSSION

4.1 Incidence of dengue

The overall incidence of dengue during 2015-2022 has been classified into different categories based on the Jenk's optimization method (Fig 4).

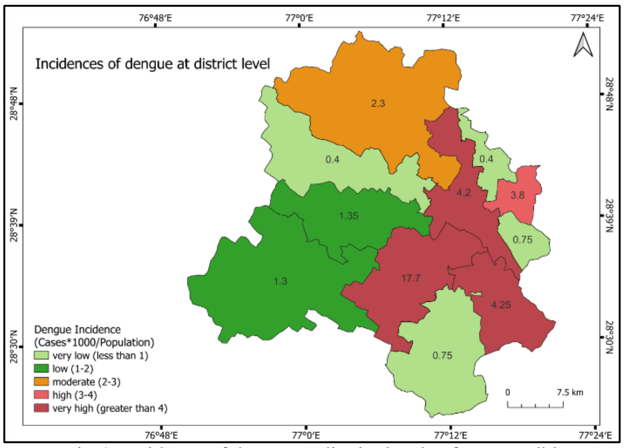

Fig 4. Incidence of dengue at district levels of NCT Delhi

The dengue incidences have been categorised into very low (less than 1), low (1-2), moderate (2-3), high (3-4), and very high (greater than 4) incidence levels. By observing the spatial distribution of dengue cases, areas with varying levels of dengue incidence may be identified. The incidence has been observed to be very high in the central region of NCT Delhi. The highly affected districts include Central, South East and New Delhi districts. The districts also have majority of sentinel surveillance hospitals. This information is crucial for understanding the geographical patterns of dengue and may aid in targeting prevention and control measures to areas with higher incidence rates.

4.2 Origin Destination (OD) Analysis

Origin-Destination analysis has been performed to study the relation between location of patients and sentinel surveillance hospitals. It has been used to understand the movement of patients based on their preference of hospital for treatment of dengue. The OD matrix has been computed between 9005 locations of patients and 35 sentinel surveillance hospitals. The output contained relations in terms of distance in km between location of patients and respective hospitals. Further, the distance has been classified into four classes (Table 1).

Table 1: Origin-Destination Analysis

Distance (km)	No. of location of cases (n = 9005)	%
Less than 5	4195	46.6%
5-10	**2357**	**26.2%**
10-15	1145	12.7%
Greater than 15	1309	14.6%

Majority of cases (46.6%) have been reported to nearby hospitals at distance less than 5km. It is followed by 357 patient locations reporting at hospitals between 5-10km of travel distance. Overall, about 85% of patients have preferred travelling distances less than 15km. A lesser number of cases have been reported at distance greater than 15 km (14.6%).

On an average, it has been observed that patients tend to prefer travelling 7.5 km since greater than this distance it has implications on healthcare accessibility and service distribution (Fig 5). It highlights the need for healthcare facilities within this range to ensure timely access to healthcare. Further, efficient transport infrastructure is crucial to facilitate patient mobility. This information aids in resource allocation and health planning for optimal healthcare provision.

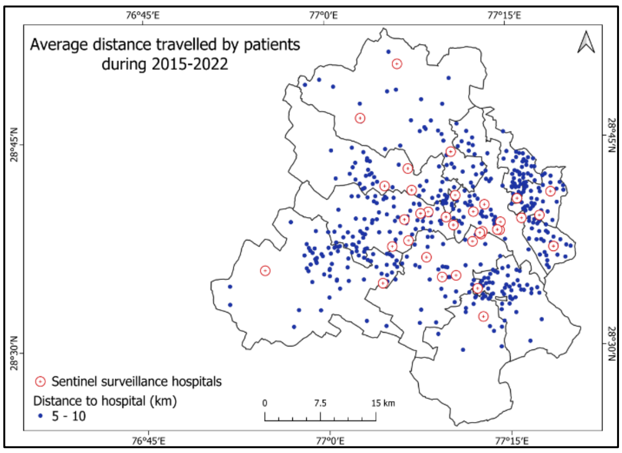

Fig 5. Preferred travelling distance by patients

4.3 Determination of Spatial-temporal clusters

After O-D analysis is performed, the spatio-temporal clusters are identified to determine the transmission pattern. The first or the primary cluster will emerge based on Kulldorf Space Scan Statistic analysis. After the primary cluster is identified, the next cluster to emerge depends upon the number of locations forming a group and that this new group is in another district at a given time interval *'t'*. Thus, process of new cluster emergence will continue till the end of dengue period. This enables to visualise how cases spread to other regions in time '*t*'. The spatio-temporal clusters for each year during 2015-2022 are shown in Fig 5-1. The emergence pattern of these spatio-temporal clusters are summarised in Table 2.

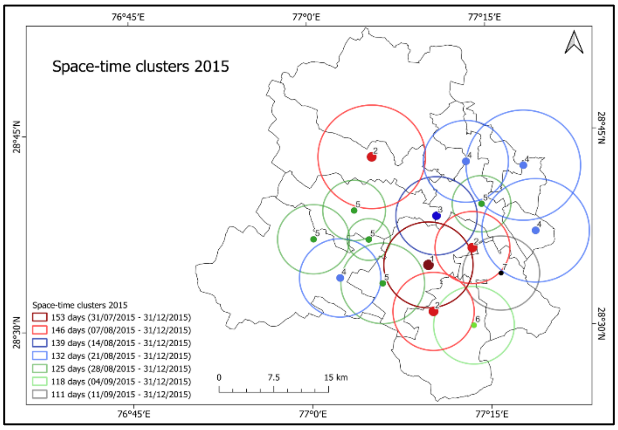

Fig 6. Spatio-temporal clusters in 2015

In 2015, it has been observed that dengue cluster emerges from ND district, the center of study area. Thereafter, two secondary clusters originate from primary cluster after 7 days, consisting of 3% of total cases. After secondary clusters, the subsequent clusters have also been observed to be formed at an interval of 7 days. This may be due to dengue transmission after a human is capable of spreading the infection to other humans (Beatty et al., 2010). The overall movement of clusters in 2015 has been observed to be in Northeast direction originated from New Delhi (ND) (refer to Fig 6 & 2) and further moved in an anti-clockwise direction.

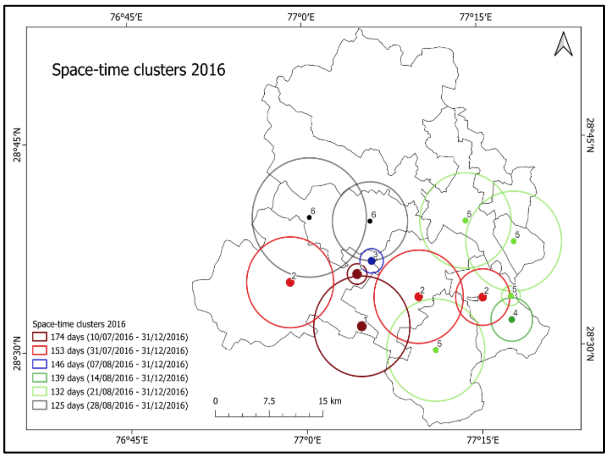

Fig 7. Spatio-temporal clusters in 2016

In 2016, two primary cluster emerge at two independent locations in South-West (SW) district around the 2nd week of October. Thereafter, three secondary clusters originate from this cluster in north-east and north-west direction respectively (Fig 7). An irregular pattern of spread has been observed as the last cluster originated adjacent to the secondary cluster after 4 weeks of its emergence.

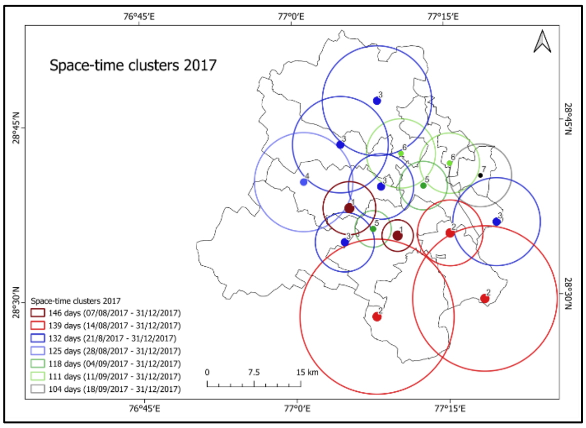

Fig 8. Spatio-temporal clusters in 2017

In 2017, the primary cluster formed at ND district as in 2015 (Table 2). The secondary cluster formed at south and south-east direction. The movement of overall cluster is observed from south in anti-clockwise direction ending at Shahdara (Sh) (Fig 2 &8).

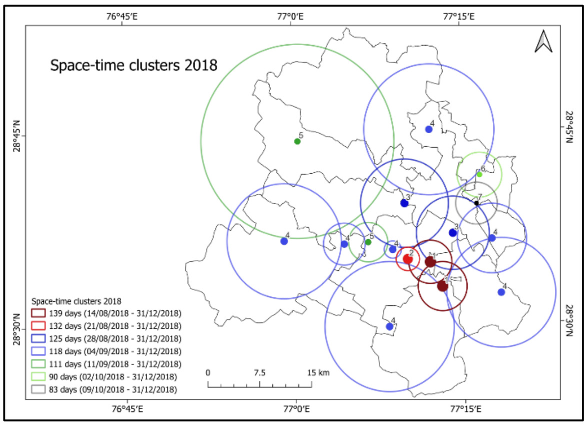

Fig 9. Spatio-temporal clusters in 2018

In year 2018, primary cluster formed again in ND district (Fig 9). The pattern of emergence of consecutive clusters in 2018 has been observed to be random in nature. Similarly, in 2019, random pattern has been observed, with clusters emerging independently at different regions after the formation of secondary cluster (Fig 10).

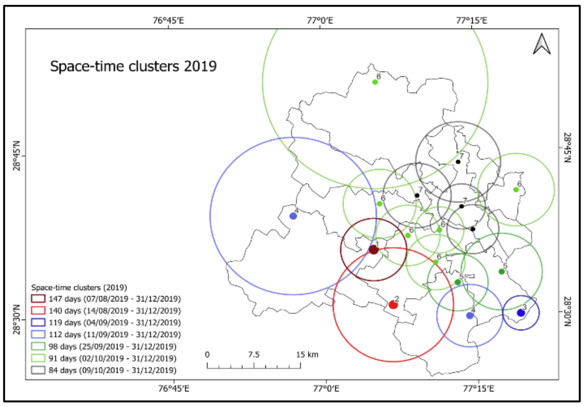

Fig 10. Spatio-temporal clusters in 2019

However, in 2020, only one statistically significant cluster has been identified. This may be due to less number of dengue cases reported during COVID-19 and that any co-infections were reported as COVID cases (National Vector Borne Disease Control Programme, 2020).

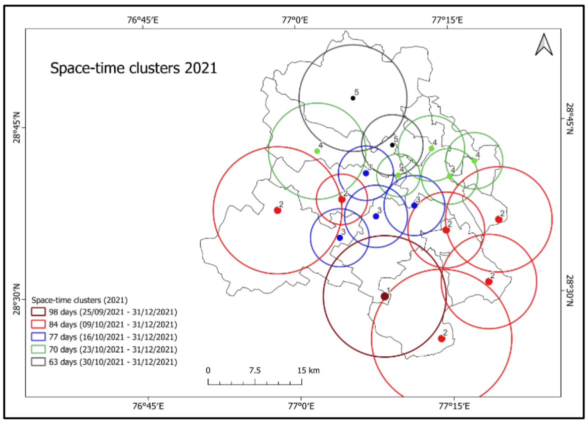

Fig 10. Spatio-temporal clusters in 2021

For the years 2021 & 2022, random transmission pattern has been also observed (Fig 11 & 12). Table 2 provides a brief of the emergence of cluster as per hierarchy of degree.

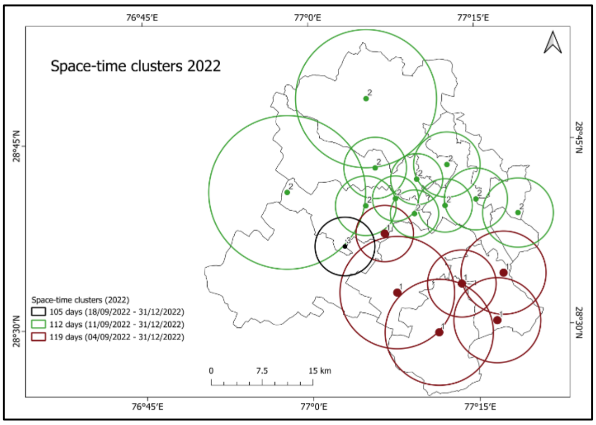

Fig 11. Spatio-temporal clusters in 2022

Table: 2 Emergence hierarchy of cluster center

Year	Stage of cluster emergence /Districts in NCT Delhi					
	1^0	2^0	3^0	4^0	5^0	No cluster
2015	ND	ND, S, NW	C	SW, E, Sh, C	C, W, ND, SW	N, NE
2016	SW	SE, ND, SW	SW	SE	E, C, S	N, NW, NE
2017	W, ND	SE, S	W, N, E, NW, SW	W	C, ND	----
2018	ND, S	ND	ND, W	C, E, S, SE, SW,	NW, ND	N, NE
2019	SE	ND	SE	S, SW	S, SE	NE, E
2021	ND	W, SW, S, SE, E	W, SW, ND	NW, C, Sh	NW, N	NE
2022	W, S, ND, SE	W, C, N Sh, NW	W	----	--	SW, E, NE

The randomness of transmission during the study period may be due to movement of people along with movement of vectors having a flight range of 200 m (Liu et al., 2019). Other factors like fluctuations in temperature, rainfall and humidity may trigger the growth of mosquitoes in poorly sanitized regions which may also affect the transmission of the disease (Telle et al., 2021).

It has been observed that during 2015-2022, the primary cluster emerges in New Delhi district. followed by W, S, SE and SW district (Fig 12). Secondary clusters have been observed to be emerged in majorly in ND district, followed by SE, S, SW, W, Sh and E districts. Based on the analysis, the average cluster stays for a period of 120 days. The overall range of temporal cluster has been observed to be between 63 to 174 days formed during the months of September to December during 2015-2022. This explains the seasonality of dengue in NCT Delhi, mostly active during rainy till onset of winters (Telle et al., 2021). The movement of people in terms of treatment has been observed to have a significant effect on dengue transmission. Based upon spatio-temporal clusters and OD analysis, ND followed by W, S, SE and SW districts are more vulnerable to dengue outbreaks. Thus, the overall direction of movement is from south to north in NCT Delhi.

Therefore, it is suggested to plan intervention measures like increase in sentinel surveillance hospitals in these districts to restrict the movement of patients. This may help reduce the spread of disease. In addition, measures like vector control, awareness and sanitation campaigns may also be adopted.

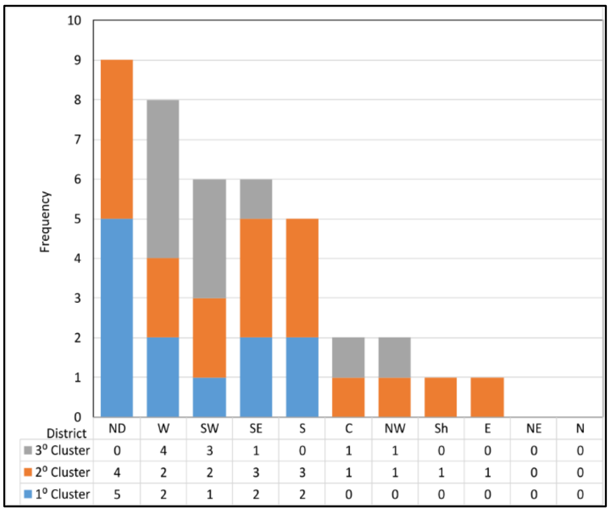

Fig 12 Frequency of districts having cluster center

5. CONCLUSION

In conclusion, this study has been able to determine the spatio-temporal transmission patterns of dengue transmission in NCT Delhi, India. Individual patient dynamics and space-time analytics have been used to visualise the pattern of emergence of clusters and its subsequent movements during 2015-2022. The overall movement has been found to be from southern to northern part of NCT Delhi. This aspect needs to be further examined. The findings of this study have significant implications for public health and evidence-based decision-making. With this knowledge, control and prevention strategies may be formulated to specific areas when transmission is most intense. It may be noted that other factors associated with dengue transmission, such as demography, vector control measures, or environmental factors, may be considered to have a holistic assessment of the dengue spread.

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References

Alshahrani, M.Y., Alamri, A.M., Alshahrani, A.S., Alshehri, A.A., Alsulaiman, A.S., Alshahrani, A.J., Dabaan, M.A., Aldhbaan, S.T., Moosa, R.A., Alkahtani, A.M., Chandramoorthy, H.C., 2021. Prevalence of selected blood-borne infectious diseases among voluntary blood donors in abha, Saudi Arabia. Southeast Asian J. Trop. Med. Public Health 52, 274–285.

Bisht, A., Kamble, M.P., Choudhary, P., Chaturvedi, K., Kohli, G., Juneja, V.K., Sehgal, S., Taneja, N.K., 2021. A surveillance of food borne disease outbreaks in India: 2009–2018. Food Control 121, 107630. https://doi.org/10.1016/j.foodcont.2020.107630

CDC, 2023. Transmission of dengue [WWW Document]. URL https://www.cdc.gov/dengue/transmission/index.html (accessed 7.6.23).

Census, 2011, 2011. Census [WWW Document]. Off. Regist. Gen. Census Comm. India Aff. Minist. Home India, Gov. India. URL https://censusindia.gov.in/2011census/population_enumeration.html (accessed 9.29.21).

Chen, Y., Zhao, Z., Li, Zhichao, Li, W., Li, Zhipeng, Guo, R., Yuan, Z., 2019. Spatiotemporal transmission patterns and determinants of dengue fever: A case study of Guangzhou, China. Int. J. Environ. Res. Public Health 16. https://doi.org/10.3390/ijerph16142486

Eames, I., Tang, J.W., Li, Y., Wilson, P., 2009. Airborne transmission of disease in hospitals. J. R. Soc. Interface 6. https://doi.org/10.1098/rsif.2009.0407.focus

Enduri, M.K., Jolad, S., 2018. Dynamics of dengue disease with human and vector mobility. Spat. Spatiotemporal. Epidemiol. 25, 57–66. https://doi.org/10.1016/j.sste.2018.03.001

Grubaugh, N.D., Ladner, J.T., Lemey, P., Pybus, O.G., Rambaut, A., Holmes, E.C., Andersen, K.G., 2019. Tracking virus outbreaks in the twenty-first century. Nat. Microbiol. 4, 10–19. https://doi.org/10.1038/s41564-018-0296-2

Liebig, J., de Hoog, F., Paini, D., Jurdak, R., 2021. Forecasting the probability of local dengue outbreaks in Queensland, Australia. Epidemics 34, 100422. https://doi.org/10.1016/j.epidem.2020.100422

Liu, B., Gao, X., Ma, J., Jiao, Z., Xiao, J., Hayat, M.A., Wang, H., 2019. Modeling the present and future distribution of arbovirus vectors Aedes aegypti and Aedes albopictus under climate change scenarios in Mainland China. Sci. Total Environ. 664, 203–214. https://doi.org/10.1016/j.scitotenv.2019.01.301

Mahabir, R.S., Severson, D.W., Chadee, D.D., 2012. Impact of road networks on the distribution of dengue fever cases in Trinidad, West Indies. Acta Trop. https://doi.org/10.1016/j.actatropica.2012.05.001

National Vector Borne Disease Control Programme, 2020. Guidelines-Mosquito-and-other-vector-control-response-2020.pdf.

NVBDCP, 2023. Dengue/DHF situation in India [WWW Document]. URL https://nvbdcp.gov.in/index4.php?lang=1&level=0&linkid=431&lid=3715 (accessed 5.2.22).

Sharma, V., Ghosh, S.K., Khare, S., 2023. a Proposed Framework for Surveillance of Dengue Disease and Prediction. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch. 48, 317–323. https://doi.org/10.5194/isprs-archives-XLVIII-M-1-2023-317-2023

Telle, O., Nikolay, B., Kumar, V., Benkimoun, S., Pal, R., Nagpal, B.N., Paul, R.E., 2021. Social and environmental risk factors for dengue in delhi city: A retrospective study. PLoS Negl. Trop. Dis. 15, 1–17. https://doi.org/10.1371/journal.pntd.0009024

WHO, 2021. Dengue and severe dengue [WWW Document]. URL https://www.who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue (accessed 6.19.21).

Wicker, S., Cinatl, J., Berger, A., Doerr, H.W., Gottschalk, R., Rabenau, H.F., 2008. Determination of risk of infection with blood-borne pathogens following a needlestick injury in hospital workers. Ann. Occup. Hyg. 52, 615–622. https://doi.org/10.1093/annhyg/men044