Chapter 20
Spatiotemporal Analysis of Dengue Infection Between 2005 and 2010

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Abstract The high incidence of dengue fever in Dhaka is a constant threat to the population and a recurring problem for the health authorities. This chapter investigates the spatial and temporal epidemiology of dengue fever between 2005 and 2010. This epidemiological analysis provided important information about the pattern of the virus cases with standard deviation ellipses being used for directional examination of the incidences. To investigate spatial dependencies and examine the occurrence pattern for clustering, Moran's *I* and Local Indicators of Spatial Association (LISA) analysis were utilised. Results showed that there was obvious spatial autocorrelation as well as significant clustering of dengue cases in Dhaka, revealing that the virus is concentrated around the heart of the city.

Keywords Dengue fever • Spatial analysis • Spatial epidemiology • Clustering

20.1 Introduction

Dengue is an arbovirus (an arthropod-borne virus), not dissimilar to yellow fever and malaria (Gubler 1998). The virus infects 50–100 million people worldwide a year, leading to approximately 500,000 severe case hospitalisations (many of whom are children); out of which about 2.5 % (12,500 people) result in death (WHO

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2012). It is one of Dhaka's most significant prevailing viral diseases (Choudhury et al. 2008).

The name dengue covers two different manifestations of the disease: classic dengue fever and dengue haemorrhagic fever/dengue shock syndrome (Erickson et al. 2010). The more common of the two, classic dengue fever, is often asymptomatic or similar to "the flu" but can sometimes cause headaches and muscle and joint pains (Erickson et al. 2010). More severe cases can progress to dengue haemorrhagic fever and dengue shock syndrome (Kalayanarooj et al. 1997).

Dengue virus infection is regarded as being emerging or re-emerging diseases for three main reasons. Firstly, the number of reported cases worldwide is increasing (through either increased infection rate or better diagnosis). Secondly, the virus has a possibly fatal manifestation if left untreated (dengue haemorrhagic fever and dengue shock syndrome), and finally, the areas endemic to the disease are expanding (Igarashi 1997).

The consequence of simple dengue fever is loss of workdays for communities dependent on wage labour. The consequence of severe illness (resulting in haemorrhage) is high mortality rates, as late stages of the virus require tertiary level management/care, which is beyond the reach of most of the people at risk (Guha-Sapir and Schimmer 2005).

Another reason for the virus's current significance is the lack of vaccine. Despite much effort, currently there is no vaccine or specific therapy for the treatment of the virus. Much of the focus has, therefore, been directed to vector control as being the main measure for virus management. Consequently, an analysis of the recorded dengue cases and an identification of risk patterns could improve decision-making for controlling the disease in an endemic region (Castillo et al. 2011).

The disease is transmitted through the bite of the *Aedes aegypti* and *Ae. albopictus* mosquitoes. These mosquitoes bite primarily during the day, especially in the hours just after dawn and before sunset, and an infection can be acquired via a single bite. A female mosquito that takes a blood meal from a dengue-infected person becomes infected itself with the virus in the cells lining its gut. About 8–10 days later, the virus spreads to other tissues including the mosquito's salivary glands and is subsequently released into its saliva. The virus seems to have no detrimental effect on the mosquito, which remains infected for life. Dengue can also be transmitted via infected blood products and through organ donation (Wilder-Smith et al. 2009).

The mosquito breeding cycle involves the laying of eggs on water, preferably in shaded and dark locations. The eggs hatch into larvae which feed on material suspended in water, eventually hatching into adult mosquitoes. The cycle from egg to adult can take as little as 7–8 days, whilst an adult mosquito lives for about 3 weeks (CDC 2012).

Many factors have been linked to the recent increase of dengue virus transmission; the main focuses being on increased urbanisation, inadequate water supply and storage and new trends in population movements (Hsueh et al. 2012; Wu 2009; Nakhapakorn and Tripathi 2005; Ali et al. 2003). In recent decades, the expansion of villages, towns and cities in endemic areas and the increased mobility of humans have increased the number of epidemics and circulating viruses. Furthermore, migration of people from lower socioeconomic groups to the cities has created slums which have poor sanitation and a deteriorating environment. Other factors affecting transmission rate include the improper dumping of rubbish such as used tyres, empty tin cans or food containers which provides breeding sites for *Aedes aegypti*.

Using GIS (Geographic Information Systems), the spatial distribution of dengue virus has been investigated in many regions of the world such as in Taiwan (Hsueh et al. 2012; Wu 2009; Wen et al. 2006), Thailand (Nakhapakorn and Jirakajohnkool 2006; Vanwambeke et al. 2006; Nakhapakorn and Tripathi 2005), Sri Lanka (Pathirana et al. 2009), Bangladesh (Ali et al. 2003), Brazil (Mondini et al. 2005; Braga 2003), Puerto Rico (Morrison et al. 1998), Saudi Arabia (Khormi and Kumar 2011), India (Bohra and Andrianasolo 2001; Bhandari 2008), French Guinea (Tran et al. 2004), Ecuador (Castillo et al. 2011) and in the United States (Erickson et al. 2010). Apart from mapping disease distribution, these studies have shown that GIS also provides a useful range of spatial analytical tools that can yield valuable information for the study of public health issues and enable health officials to plan for informed decision-making (Rezaeian et al. 2007).

The World Health Organization (Martinez 2007) has explained how GIS and related geospatial technology has the potential to aid in worldwide dengue prevention and control programmes. It gives the relevant personnel the ability to organise and link datasets from different sources. This enables them to access data from GPS receivers and digital imagery from satellites and aerial photos. Remote sensing can provide up-to-date information on soil moisture, vegetation type, land cover/use, urban planning, crop monitoring, forestry and water and air quality that influence the vector-borne disease occurrences. It also provides the capabilities for authorities to synthesise and visualise information in maps.

The aim of this chapter is to present a straightforward approach using spatial techniques to investigate and evaluate the spatial pattern of dengue virus in Dhaka between the years of 2005 and 2010. Our intention was to determine whether dengue virus cases in Dhaka are clustered or conform to the pattern known as complete spatial randomness.

20.2 Data and Methods

20.2.1 Data

Data on dengue cases for the period of 2005–2009 and the first half of 2010 was obtained from the record rooms of 11 major health service providers in Dhaka megacity (see Chap. 19) with a standardised patient abstraction form that includes date of admission, location of patient's residence, demographic and clinical data and date of discharge and outcome (dead/alive). Only those admitted to hospital with dengue fever were included in the database, and outpatients were excluded. The diagnosis of dengue was made by physicians at the respective hospitals, and some, but not all, were confirmed by laboratory investigation. To avoid data duplication, we first matched data in the case records using all the demographic variables and then cross-checked the data against the corresponding day/year in the logbooks of the hospitals. If a case occurred in both these records, then we included it in the database. We excluded cases residing outside of the study area (see Chap. 1) along with duplicates which resulted in a total of 3,169 dengue cases being available for analysis. Census tracts, the lowest level of census geography in Bangladesh, were used as a geographic data. Case mapping, creation of geographic feature dataset and encoding method were performed using procedures described elsewhere (Dewan et al. 2013).

Population data from the 2001 census, including a breakdown into male and female categories within different age groups, were obtained from the Bangladesh Bureau of Statistics community series (BBS 2003). Since the data were in tabular format, they were first encoded in a spreadsheet and then linked with the geographic unit by using a unique ID.

20.2.2 Analytical Techniques

GIS modelling has been used to investigate disease patterns in a number of different areas using a number of different methodologies. Morrison et al. (1998), for example, performed a space-time analysis of reported dengue cases during an outbreak in Florida and Puerto Rico in 1991–1992. Pratt (2003, p. 2) discussed how "incorporating traditional epidemiological statistical techniques into a GIS interface allows researchers to gain a greater insight into the spatial aspect of the spread of disease".

A study by Nakhapakorn and Tripathi (2005) followed two main processes for the analysis of dengue. Firstly, the relationship between cases and the areas' climatic variables was evaluated through multiple regressions, and then an Information Value approach was used to determine which physical and environmental factors are more crucial in dengue incidences. Mondini et al. (2008) examined the spatial correlation between dengue incidents and socioeconomic, demographic and environmental factors in a city in Brazil, whilst Haddow et al. (2009) claimed to be "the first use of smoothing techniques, the global Moran's *I*, and the Local Indicators of Spatial Association (LISA) to detect spatial clustering of La Crosse virus infections at a national level in the United States". More recently, Hsueh et al. (2012) examined the spatiotemporal patterns of dengue fever in Kaohsiung City, Taiwan. Their study focused on three main variables (density, transportation arteries and water bodies) and confirmed to some degree the importance of these variables in the spread of dengue fever.

The methodology used in this study comprises three major parts: data processing and inspection through visualisation, statistical testing to perform epidemiological analysis and spatial analysis employing autocorrelation techniques and cluster pattern identification.

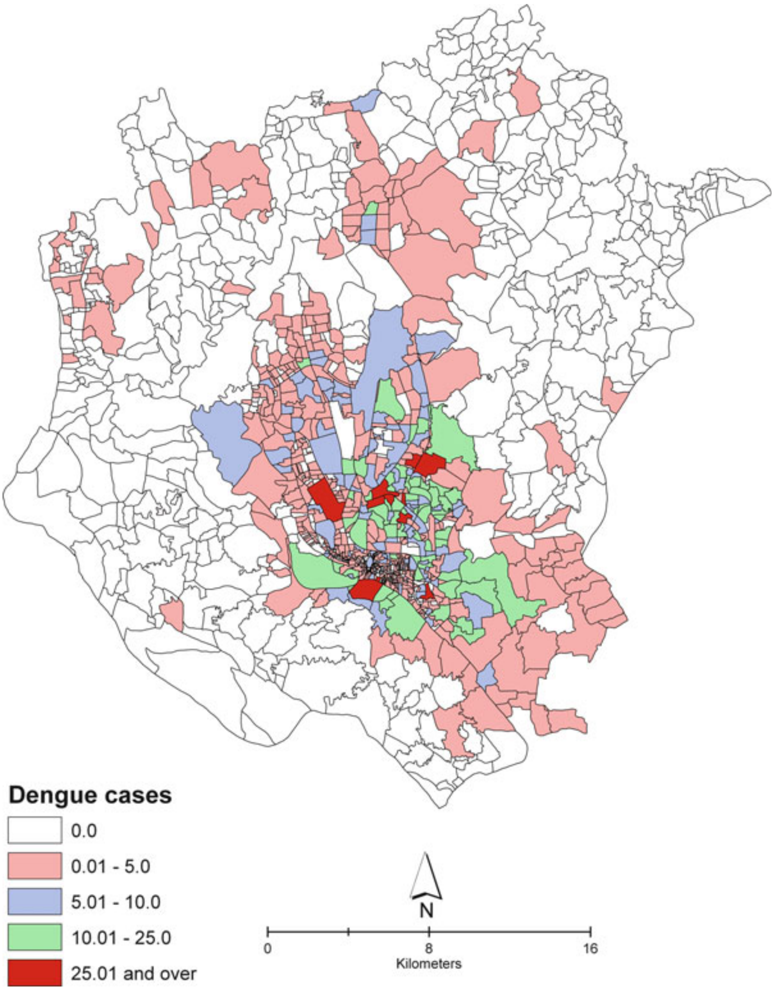


Fig. 20.1 Frequency of dengue cases by census tract, 2005–2010

Visualisation is an important tool for showing the change in disease patterns over time. An initial infection occurrence map was produced using ArcGIS 10 software (ESRI 2011), with appropriate symbolisation and a suitable number of classes. The resulting map (Fig. 20.1) portrays the frequency of virus occurrence over the region for the study period. The main data file comprised 3,169 dengue cases over a five-and-a-half-year period, attributed according to sex, season and age group. Using the SPSS software (SPSS Inc 1999), the data were initially analysed by year and season, to determine any obvious temporal pattern, and then by the patient's sex and age group, to determine any socio-statistical relationships. The dependent variables used for this section were the recorded frequency counts for the virus throughout the study period. The one exception to this is that in the case of the standardised age-specific incidence analysis – the independent variable used was not frequency count but rather the age-standardised incidences, computed as the ratio of the virus count for each age group to population count of each age group, standardised for a population of 100,000 people.

In order to visualise the directional diffusion of the virus, standard deviation ellipsoids were derived to show whether or not the dengue occurrences followed a directional pattern over the region and how this pattern moved over the years. This was carried out using the Directional Distribution (standard deviational ellipse) tool in ArcGIS 10. This process calculates the standard deviation of the x and y coordinates differences from the mean centre to define the axes of the ellipse (ESRI 2012). The orientation of the major axis of the standard deviation ellipse is that rotation from geographic north which minimises the sum of the squares of the deviation of the features from the axes. This can guide the analyst in terms of which regions to focus on, and whether or not directional analysis should be considered in later studies (Blewitt 2012). Due to the size of the study area, standard deviational ellipses with a radius of two standard deviations were computed, allowing for a wider directional perspective.

Spatial autocorrelation testing was used as a measure of the degree to which the occurrence data are clustered/dispersed together in space. The Moran's *I* index was used in this study. This index can typically be applied to area units where numerical ratio or interval data is used and yields an overall value for the whole dataset.

Moran's *I* is defined as

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i \neq j} \sum w_{ij}\right)\left(\sum_{i=1}^{n} (x_i - \bar{x})^2\right)} \tag{20.1}$$

where n is the number of spatial units indexed by i and j, x is the variable of interest, w is an element of a matrix of spatial weights and x_i is the value of the interval or ratio variable in area unit i. The value of Moran's I ranges from -1 for negative spatial autocorrelation to $+1$ for positive spatial correlation.

The weights matrix can be constructed based on the contiguity (adjacency) of the polygon boundaries or calculated from the distance between polygons centroids. For this analysis, queen's case contiguity was used, with a weight of 1 implying that polygons are adjacent and a weight of 0 implying non-contiguity.

Finally, the geographical pattern of the occurrence points was examined in more detail using the Local Indicators of Spatial Association (LISA) measure. LISA is a local autocorrelation measure proposed by Anselin (1995) to assess spatial autocorrelation and identify regions with disease rates statistically similar to and dissimilar from their neighbours. LISA analysis yields a measure of spatial autocorrelation for each individual location and allows us to identify high-high clusters (hotspots) in an area indicating the area's high values of a variable that are surrounded by high values on the neighbouring areas, as well as the low-low clusters (cold spots) which are areas of low values of a variable surrounded by low values. The procedure is implemented in the GeoDa software (Anselin et al. 2006).

The definition of the LISA measure is given below:

$$I(i) = \frac{x_i - \overline{x}}{\delta} \times \sum_{j=1}^{n} \left[W_{ij} \times \frac{(x_j - \overline{x})}{\delta} \right] \tag{20.2}$$

where $I(i)$ is the LISA index for region i, w_{ij} is weight describing the proximity of region i to region j, $x_i - \overline{x}$ is the deviation of region i with respect to the mean, $x_j - \overline{x}$ is the deviation of the region j with respect to the mean, δ is the standard deviation and n is the total number of the regions to be evaluated. The weights w_{ij} are set so that if region i is adjacent to region j, a value of 1 is assigned; a value of 0 is assigned otherwise. Adjacency may be assigned in a number of ways, usually in relation to the hypothetical movements of chess pieces (Anselin 1995).

In this study, as for the Moran's I calculations, the dependent variable used was total frequency of dengue cases for the study area with adjacency defined as being "queen's case". The GeoDA implementation of LISA uses a randomisation technique to infer significance of the results (Anselin 2003, 2004). Inference for significance of both global and local Moran's I was based on 499 permutations with an alpha level of 0.01 to test the statistical significance.

20.3 Results

20.3.1 Visual Inspection

Figure 20.1 is a choropleth map showing the total dengue frequency in the study period for each census tract with five classes determined by using a natural breaks algorithm. The map shows that the dengue cases are most common closer to the centre of the city with fewer occurrences towards the outer limits of the city.

Table 20.1 suggests that over the study period, there has been a general downward trend in dengue cases, with the exception of 2008, when recorded occurrences increased by 63 cases.

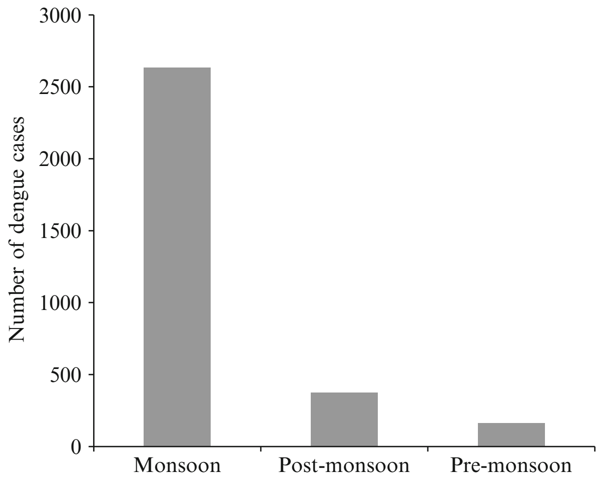
20.3.2 Epidemiology of Dengue

The monsoon season in Bangladesh runs from July to October, and the post-monsoon season (winter) defines from November to February, and the pre-monsoon season from March to June. Figure 20.2 shows the difference in seasonal distribution of the dengue virus. It is evident that the dengue virus is most active during the monsoon, with a few residual cases before and after. During

Table 20.1 Annual dengue occurrences, 2005–2010

Year	Number of cases	Percent (%) of total	Cumulative percent (%)
2005	727	22.9	22.9
2006	584	18.4	41.4
2007	497	15.7	57.1
2008	560	17.7	74.7
2009	421	13.3	88.0
2010	380	12.0	100.0
Total	3,169	100.0	

Fig. 20.2 Seasonal distribution of dengue occurrences



this monsoon period, very heavy rainfall lashes the city as well as the entire country, providing excellent damp breeding sites for the *Aedes aegypti* mosquito to thrive in.

Further descriptive analysis shows that there is a considerable difference between the number of male and female dengue cases over the years. From 3,169 recorded dengue patients, 72.6 % of total (2,301) were male, giving a male/female ratio of 2.65:1.

Table 20.2 shows that the age group of people most affected are between 18 and 34. This may be attributable to the fact that they are the most mobile and likely to be involved in the workforce. The next most affected age group is 35–59, closely followed by infants 0–4. The mean age of the dengue cases is within the 18–34 age group, whilst the median age (26) also lies in the same category. Surprisingly, our data does not show any cases for the age group of 5–9. This is similar to the result found for the prevalence of typhoid case in the same area (Dewan et al. 2013).

In analysing the number of deaths recorded in the data, we found that out of the 3,169 patients, almost 8 % (251 instances) of dengue cases resulted in death from the haemorrhagic complications of the disease, whilst 80 % (2,538 instances) of all cases reported being nonfatal classic dengue fever (the outcome is unknown for 2 % of the cases). Examining this in more detail, we found that the largest number of

Table 20.2 Standardised age- and gender-specific incidences

Age	Sex	Cases (%)	Population	Annual incidence rate (per 100,000)	Annual incidence rate for both sex
Total	Male	23,011 (72.6)	4,548,189	506.94	289.60
Total	Female	868 (27.4)	3,697,393	23.48	
0–4	Male	244	401,545	60.77	47.70
	Female	119	359,439	33.11	
10–14	Male	43	482,972	8.90	6.16
	Female	15	458,050	3.27	
15–17	Male	140	279,568	50.08	36.15
	Female	50	246,056	20.32	
18–34	Male	1,223	1,752,085	69.80	52.03
	Female	432	1,428,841	30.23	
35–59	Male	579	1,048,331	55.23	47.38
	Female	209	614,674	34.00	
60+	Male	67	183,561	36.50	34.52
	Female	40	126,443	31.63	

deaths from dengue is amongst the working age group (18–34) with 132 (53 % of total deaths) cases, followed by the 35–59 age groups with 65 total cases (25 %). However, the 0–4 age group had the highest number of deaths relative to the number of recorded cases in that age group, with 31 (12 %) out of 52 cases resulting in death. The 10–14 age group only made up 1 % of deaths, whilst the 15–17 and 60+ age groups together made up the remaining 9 %.

20.3.3 Spatial Analysis

A frequently used method of visualising the spatial trend, through time, of the attributes of a set of points or areas is to calculate the standard deviation of the points for each year. Figure 20.3 shows the overlapping standard deviational ellipses of the dengue occurrences per census tract over the years 2005–2009 (half-year data for 2010 excluded), each year being represented by a different colour. This shows that the dengue occurrences follow a diagonal South-South Easterly to North-North Westerly pattern with little change over the years.

Figure 20.4 shows the scatterplot results for the autocorrelation test carried out using GeoDa for each year of the dengue occurrence data. The Moran's *I* spatial statistic is visualised as the slope of the scatterplot with the spatially lagged variable on the vertical axis and the original variable on the horizontal axis. The slope of the regression line is Moran's *I* statistic and is shown at the top of each window.

In all instances, adjustment for outliers (highlighted with yellow in each diagram) was made. However, this had little overall impact as outliers were few and

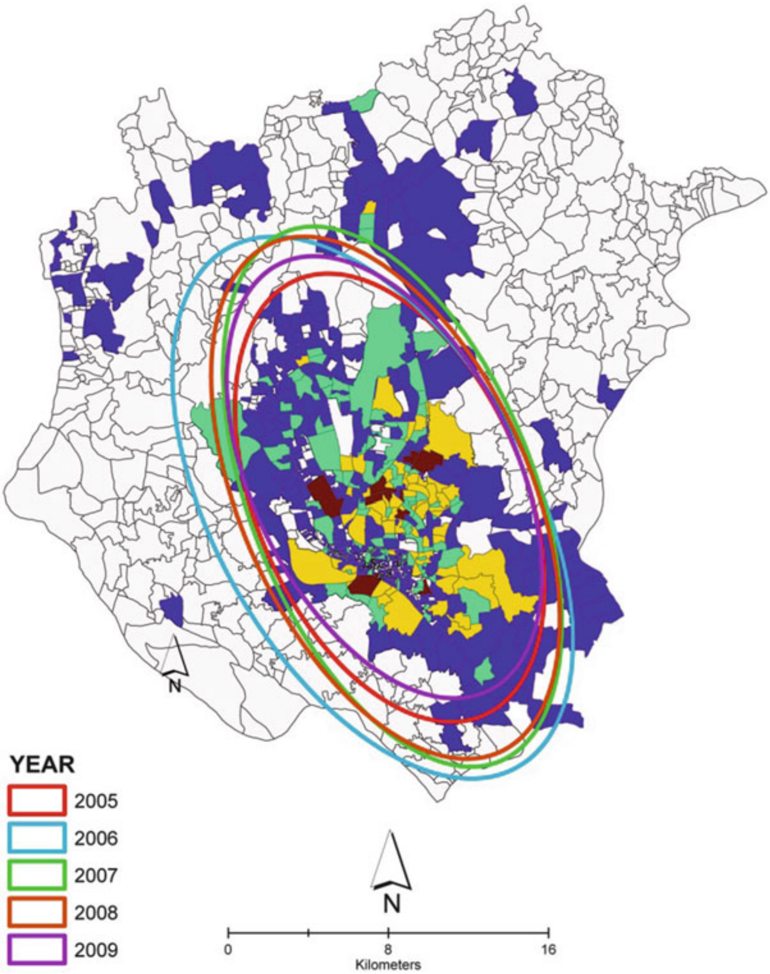


Fig. 20.3 Standard deviation ellipsoids of dengue occurrences, 2005–2009

insignificant. The scatter plots show that the actual dengue cases (x-axis) were positively correlated with the spatially lagged cases (y-axis) and follow a clustered pattern.

To assess the significance of the Moran's I statistic against a null hypothesis of no spatial autocorrelation, GeoDa uses a permutation procedure; in this case 499 permutations were used. Since each set of permutations is based on a different randomisation, the results will not be exactly replicable.

Results for the statistical significance testing is shown in Table 20.3, which shows significant positive spatial autocorrelation in dengue occurrences for the first 5 years recorded, with Moran's I statistics of 0.36 ($p = 0.01$) in 2005, 0.25 ($p = 0.01$) in 2006, 0.23 in 2007 ($p = 0.01$), 0.31 ($p = 0.01$) in 2008 and 0.42

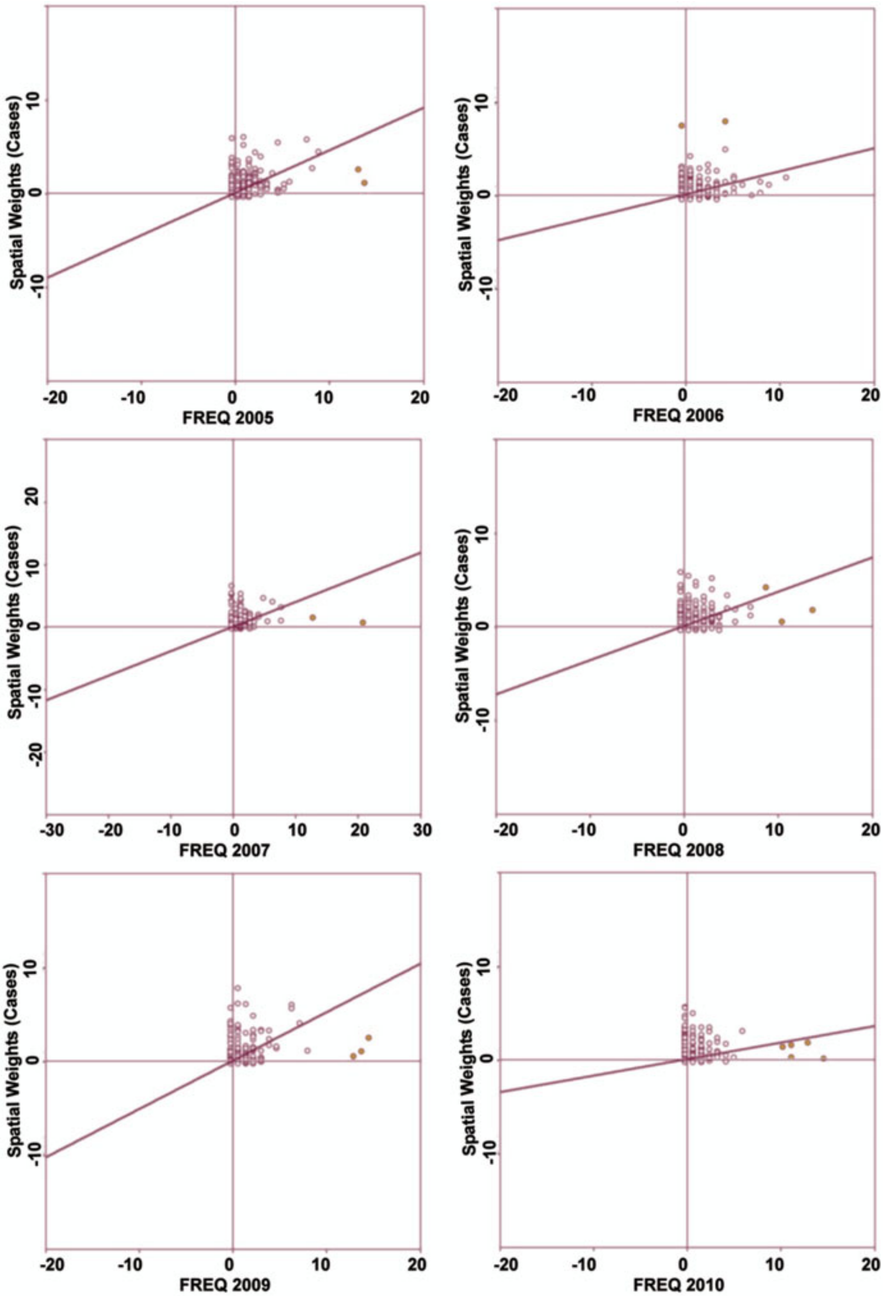


Fig. 20.4 Moran's *I* scatterplots for total dengue frequency, 2005–2010

Table 20.3 Spatial autocorrelation for dengue, 2005–2010 (non-outlier adjusted)

Period	Moran's I	Mean	SD	$E[I]$	p-value
2005	0.3578	−0.0018	0.0158	−0.0008	0.01
2006	0.2463	−0.0016	0.0195	−0.0008	0.01
2007	0.2259	−0.0027	0.0165	−0.0008	0.01
2008	0.3056	−0.0029	0.0197	−0.0008	0.01
2009	0.3204	−0.0005	0.178	−0.0008	0.01
2010	0.1751	−0.0018	0.0166	−0.0008	0.01

($p = 0.01$) in 2009. Whilst the 2010 data does not follow this trend, results for this year are deemed unreliable since they are from an incomplete year.

Since the Moran's I global spatial autocorrelation statistic indicated a clustered pattern of dengue cases in Dhaka, the analysis proceeded to investigate that pattern further. The LISA analysis produces two maps: a cluster map and a significance map. The combination of the two allows us to see which locations are contributing most strongly to the local outcome and in which direction.

The cluster map for dengue occurrences is shown in Fig. 20.5. The map distinguishes between clusters of high values, shown in red, which also have neighbours of high values (HH); clusters of low values, shown in blue, with low-value neighbours (LL); outliers, in pink, where a high value is surrounded primarily by low values (HL); and outliers, in pale blue, where low value is surrounded primarily by high values (LH). The strongly coloured regions on the map are therefore those that contribute significantly to a positive global spatial autocorrelation outcome, whilst paler colours contribute significantly to a negative autocorrelation outcome.

Figure 20.6 shows the statistical significance level of each region's contribution to the local autocorrelation outcome. This was determined using an automated complex Monte Carlo randomisation procedure (O'Sullivan 2012).

20.4 Discussion

The data visualisation provides a perspective on the nature of the disease in Dhaka megacity. Hanafi-Bojd et al. (2012) discuss how the maps produced by their study provided a visual tool for decision-making about initiating and focusing control programmes for malaria in Iran. However, whilst visualisation may be a powerful tool for providing a "bigger picture" perspective, it is still only a stepping stone to further analysis. As Wen et al. (2006) explained in a similar dengue study, visualisation cannot definitively confirm clustering of cases or spatial correlations.

The results for the epidemiological analysis show that dengue incidences had a yearly decreasing trend except in 2008. This may be due to higher virus awareness, changing environmental conditions or even more use of control measures in publicly accessible mosquito breeding sites. However, reporting on dengue in

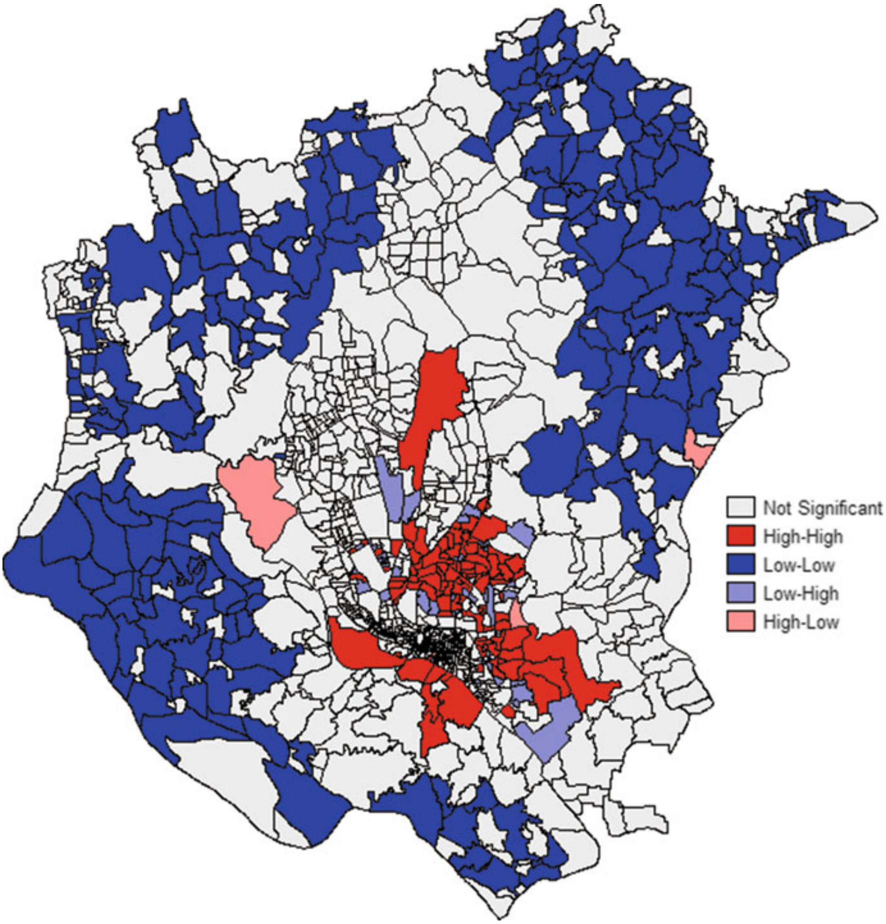


Fig. 20.5 Spatial clustering of dengue, 2005–2010

Dhaka, the United Nations Environmental Programme (2006) stated, "Even though the incidence of dengue fever has decreased, the mosquito problem prevails" (UNEP 2006, p. 62).

In the seasonal analysis, a significant difference in seasonal distribution of the dengue virus is noted, with cases being concentrated during the monsoon season where rainfall is significantly heavy in the region. This concurs with findings by Ahmed et al. (2007, p. 209) which showed that "the seasonal pattern of the mosquitoes was fairly close to variations in rainfall [...] the highest rainfall indicated the highest larval population except in May, which is the starting time of the rainy season in Bangladesh". Other studies related to the *Aedes aegypti* mosquito have shown similar seasonal patterns. Vezzani et al. (2004) found that the highest *Aedes aegypti* density was associated with accumulated rainfall above

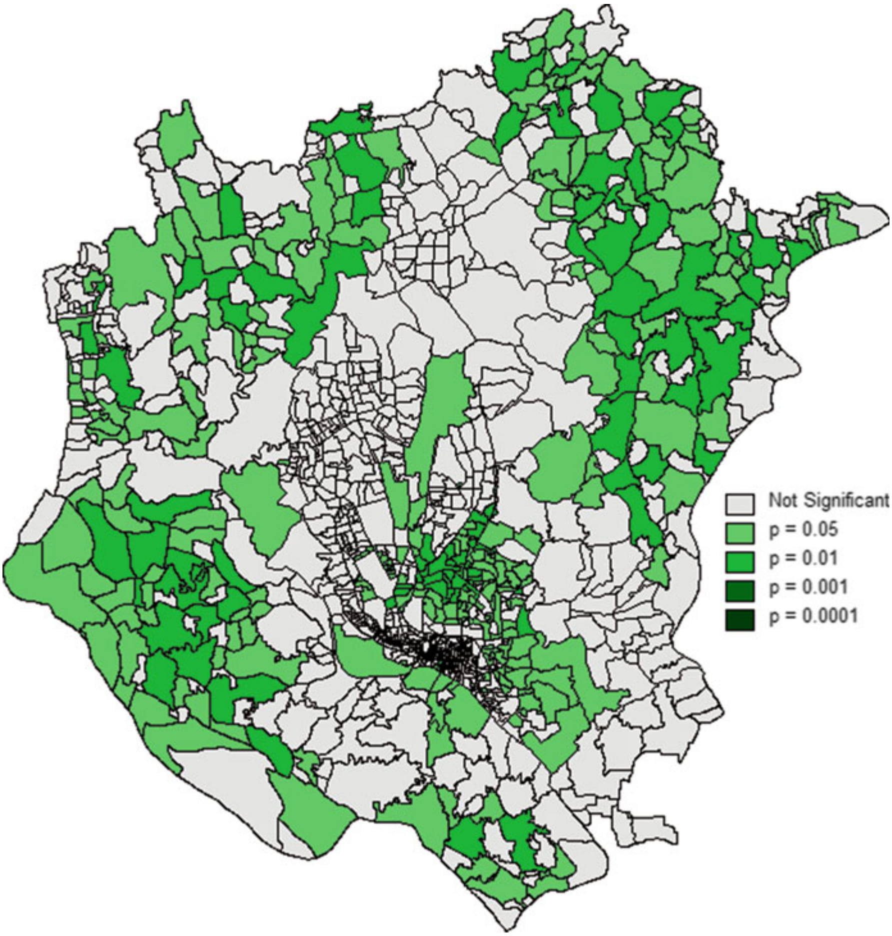


Fig. 20.6 Dengue significance map

150 mm. Micieli and Campos (2003) observed the close relationship of the highest peak of *Aedes aegypti* population with high rainfall and the fact that the mosquito population decreased during months with less rainfall. Additionally, Hashizume et al. (2012) presented strong evidence indicating that dengue fever increased with river levels, proving that factors associated with both high and low river levels increase the hospitalisations of dengue fever cases in Dhaka.

In regard to the significantly higher percentage of male patients than female patients, we propose two possible explanations. One is that men are more exposed to dengue-carrying mosquitoes during the daytime either at the workplace or whilst travelling to and from work. The other is that adult men are more likely to seek health care than adult women. A similar finding has been reported for typhoid incidence in the same area (Dewan et al. 2013). Anker and Arima (2011) have elaborated further on this issue in a paper looking at gender differences in dengue cases in six Asian countries.

It is widely recognised that in many of the Asian communities, lower disease incidence in women may be a statistical artefact related to lower reporting and to women seeking care from traditional practitioners who do not report to public surveillance systems. By the same token, women are less likely to be taken for care at a hospital when ill or are taken at late stages of disease, when no other options are available. Determining gender differences, both in infection and severity of disease, requires well-designed and targeted studies to capture both the biological and social factors that drive disease patterns in a community (Guha-Sapir and Schimmer 2005). Furthermore, dengue is typically regarded as a childhood disease and is an important cause of paediatric hospitalisation in Southeast Asia. Severe disease in Southeast Asia is also common in babies and young children, as found in this study, due to their low immunity (Ranjit and Kissoon 2011).

Whilst it is possible to get a general sense of the spatial orientation of cases by plotting a simple choropleth map such as Fig. 20.1, the use of standard deviation ellipses makes the trend clear. By looking at the orientation and size of standard deviation ellipses for several years, it is possible to predict which areas should prepare for a rise in incidence of that disease (Blewitt 2012), or whether the pattern remains largely static over time.

The global spatial autocorrelation analysis using Moran's I showed that the distribution of dengue virus was spatially clustered, for all years with complete data. The scatter plots indicated the presence of spatial dependence across the years. The highest indices were observed for the years 2005 and 2009 (0.45 and 0.5 ($p = 0.01$), respectively (after outlier elimination)), with the rest of the years remaining around the 0.3 value ($p = 001$). It is not unusual for data of an infectious disease, like dengue, to have a strong clustered spatial pattern due to the method of propagation of the disease involving proximity and neighbourhood (Jeefoo et al. 2011). This information corresponds with the public health opinion that dengue mainly occurs in clusters and does not spread regularly or randomly throughout the area (WHO 2009). There are many reasons as to why dengue occurrences appear to be strongly clustered around the heart of Dhaka City: urbanisation and population density (Wu 2009; Bhandari et al. 2008; Hsueh et al. 2012; Khormi and Kumar 2011; Ali et al. 2003), land use (Pathirana et al. 2009; Vanwambeke et al. 2006), presence of standing water and impervious surfaces in a high rainfall area (Pathirana et al. 2009), and socioeconomic factors relating to literacy and correct management of water awareness (Mondini and Neto 2008).

It is instructive to compare the land use maps shown in Chap. 5 with the cluster map in Fig. 20.5. This shows an apparent correspondence between the areas with a dense combination of both built-up and vegetation land use areas and the disease case count. However, this relationship requires further examination as this apparent causality may be due to multicollinearity of several external variables and needs to be tested further.

20.5 Conclusions

The incidence of dengue fever in Dhaka is a constant threat to the population and a recurring problem for the health authorities. Through spatial autocorrelation, clustering and epidemiological analysis, this chapter examines the spatial and temporal distribution of dengue cases in the study area. It identifies potential dengue risk areas in the city based on recorded virus frequency for 2005–2010. We have shown that there is a clear pattern of clustering to dengue virus occurrences in Dhaka.

The spatial distribution of dengue occurrences was observed to follow a geographically clustered pattern. This was confirmed by statistical testing using Moran's I which indicated strong autocorrelation within the data. The largest clusters of dengue cases were present around the centre of the city and around the heavily urbanised regions of the city. Whilst this may seem to suggest that the highest rate of dengue illness in Dhaka occurs in areas of high urbanisation, this is an incomplete picture.

Overall, the spatial analyses that were carried out were capable of identifying simple relationships within the data and will need to be taken further in order to effectively bring about more census tract-specific findings. This would require consideration of both the effects of urbanisation and other socioeconomic and biophysical factors in the region. Further analysis could assist in focusing and implementing precautionary and preventive strategies to more effectively monitor and control the incidence of dengue.

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