Socio-demographic heterogeneities as determinants of water and food-borne disease burden in Ahmedabad City, India

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Abstract

Urban areas within low and middle-income countries (LMICs) represent a confluence of unique and complex risk factors influencing disease dynamics. Continuous growth in the urban population fueled by migration and informal settlements makes these urban city centers conducive to inequality, environmental hazards, and infectious diseases. In this study, we evaluated the relationship between socio-demographic risk factors (age/gender, slum population density, and illiteracy rates) and spatial heterogeneity in the prevalence of viral hepatitis, typhoid, and diarrhea in Ahmedabad, India, from 2010 to 2017. The geographical distance of the wards from the river was also considered a potential risk factor. The analysis suggested positive spatial autocorrelation for viral hepatitis, typhoid and diarrhea incidence. The results of the Ordinary Least Square (OLS) and Spatial Lag Regression (SLR) models identified slum population density as a significant risk factor for all three diseases. Further, we observed a positive association between illiteracy rate and spatial distribution of viral hepatitis and typhoid at the local level, while the proximity of the wards to the river was associated with the incidence of viral hepatitis. In addition, the excess risk mapping of diseases revealed that most of the *hotspot* wards were in the central and southern zones of the city, to the east of river Sabarmati. This study identified issues arising due to spatial heterogeneities of resources and population demography. It thereby emphasizes rehabilitation, capacity building, and health systems strengthening through micro-planning at sub-ward/ward levels, as prospective solutions for health concerns arising from the urban paradigm.

Introduction

Infectious diseases are linked to considerable morbidity and mortality worldwide^{1,2}. It continues to pose a public health threat with considerably higher burden in low and middle-income countries (LMICs), especially for the weaker sections of society³. The prevalence of infectious diseases in India between 2004 to 2014 was 29.57 per 1,000 population⁴. Even though the prevalence of infectious diseases in India has remained stagnant over the past few years, some states are still experiencing a prominent burden of it, and the rural to the urban transition of infectious diseases between 2004 to 2014 is a cause of concern for health authorities⁴.

Demographic shifts of the population in the LMICs are responsible for fluctuating transmission of diseases⁵. Technological development, environmental change, and rapid population growth have a profound effect on global health and impact the burden of infectious diseases in developing countries⁶. Continuous population migration into cities sets off the chain of inequality, environmental hazards, and, thereby, infectious diseases⁷. Cities in developing countries experience unplanned urbanization, which gives rise to informal settlements or *slums* and population congestion. Communities living in these settings are often characterized by rapid urbanization, demographic shift, and lack of basic municipal infrastructures and are particularly vulnerable to threats of infectious diseases⁸. Therefore, in-migration and burgeoning of city populations lead to multi-faceted exposure mechanisms to infectious disease transmission among the urban-poor population, straining public health systems and resources.

In a theoretical sense, an urbanized environment ought to reduce infectious disease burden by rendering better civic amenities; however, empirical evidence has depicted an elevated risk of infectious diseases in cities, possibly due to consequences stemming from poor sanitation and overcrowding^{5,9}. In fact, prior studies have shown that infectious disease burdens in urban settings are influenced by a myriad of risk factors, including social/economic¹⁰, sanitation¹¹, population demography¹², nutritional status¹³, lack of awareness¹⁴, and education^{14,15}.

As per Global Burden of Diseases (GBD) 2019 estimates, the disease burden of enteric infections in India is 5.3%, while diarrheal diseases are around 4%¹⁶. Typhoid, diarrhea, and viral hepatitis, which usually present as infectious diarrhea, share a common oral-fecal transmission route associated with poor sanitation and hygiene¹⁷. However, there is a paucity of data about how the incidence of these diseases vary within a metropolitan area and the extent through which such heterogeneity can be attributed to the underlying inequalities and other socio-demographic factors. Therefore, this paper aims to explore how the incidence of food and water-borne illnesses (viral hepatitis, typhoid, and diarrhea) in Ahmedabad varies across socio-economic, geographic, and environmental risk factors. Characterizing spatial heterogeneity of diseases within cities delineates their space-time variations and identifies target 'hotspots' for interventions. This can be vital to delivering efficient policy discourses for reducing the disease burden.

Material And Methods

Study area

Ahmedabad (23.03° N, 72.58° E) is the seventh-largest agglomeration in India, encompassing an area of 466 Sq.km. with a population of 5.6 million¹⁸. The city is located along the banks of river Sabarmati with seven administrative zones and 48 wards, as shown in Fig. 1. The slum population of the city has also grown by 80%, from 439,843 in 2001 to 798,206 in 2011, and constitutes 14% of the city's population¹⁹. The city is divided into two halves by the river Sabarmati – the eastern part accommodates the old city, and the western part accommodates the new city. The climatic condition can be described as semi-arid, primarily hot and dry except during the monsoon season.¹⁸ The city is the commercial center of Gujarat with booming construction and is a rising center of education, information technology, and industries. Along with rapid infrastructural development, the city has also experienced unplanned urbanization and migration, making the environment conducive for the spread of water-food-borne diseases.

[FIGURE 1]

Data collection

Monthly, ward-level (administrative units, 57 health wards) data of hepatitis A (viral hepatitis), typhoid, and diarrhea which are among the most common diarrheal diseases, were obtained from the Epidemic Cell of the Health Department of Ahmedabad Municipal Corporation (AMC) from January 2010 to

December 2017. Because some wards are divided into smaller wards by the health department for administrative convenience, the data were aggregated into 48 census wards to maintain sync with census population data. All viral hepatitis, typhoid, and diarrhea case numbers represent cases that were self-reported to health centers and hospitals and confirmed by medical officers. Short-lived cases of acute diarrhea were diagnosed as Acute Diarrhoeal Disease (ADD). Longer-lasting cases of fever with or without diarrhea and cases of jaundice were prescribed widal or HBsAg testing, respectively. Laboratory confirmed widal positives and HBsAg negative cases were regarded as typhoid and viral hepatitis (mostly Hepatitis A and E), respectively. Cases reported from larger public hospitals and a few private hospitals and private labs were allocated to respective health wards, based on registered addresses and a confirmatory visit by a local health worker to verify the presence of each of the cases in specific health wards.

The socio-demographic profile of the city based on the 2011 census was retrieved from the open-source of the Office of the Registrar General & Census Commissioner. The numbers of cases of the three diseases in each ward were normalized per 100,000 population. The socio-demographic risk factors of gender, 0–6 years children and illiteracy were also adjusted for population. The distance of the Sabarmati river (in km.) from each ward was calculated using QGIS 3.30.2 software. As shown in Fig. 1, the AMC ward facilities office was used as the central point to calculate this distance.

Statistical modeling and analysis

Temporal and spatial variation patterns

An initial spatial mapping of diseases was done for the entire study period i.e., 2010–2017 to evaluate the spatial variation of diseases using QGIS version 3.20.2. Disease maps of each study year were also generated to understand the temporal variation of diseases. In addition, to understand the characteristics of each ward, socio-demographic variables were also mapped.

Moran's I statistics were calculated for each disease using the GeoDa version 1.80 to check spatial clustering or randomization of diseases²⁰. Moran's I is a correlation statistic between a variable and its spatial lag, with the variable expressed in deviations from its mean. For example, for observation at location i , it is expressed as $z_i = x_i - \bar{x}$ where $\bar{x}$ is the mean of variable x .

Moran's I statistic is then:

$$I = \frac{\sum_i \sum_j w_{ij} z_i z_j / S_0}{\sum_i z_i^2 / n} \quad (\text{Eq. 1})$$

with w_{ij} as the elements of the spatial weights matrix, $S_0 = \sum_i \sum_j w_{ij}$ as the sum of all the weights, and n as the number of observations, the Queen Contiguity weight matrix created using GeoDa 1.80 version was used in the analysis as a spatial weights matrix. The Queen Contiguity weight matrix identifies neighboring units based on both common boundaries and corners. The nature of the spatial

autocorrelation was checked using Moran's I scatter plots. The upper-right quadrant and the lower-left quadrant correspond with *positive* spatial autocorrelation i.e. similar values at neighboring locations and are referred to as *high-high* and *low-low* spatial autocorrelation. In contrast, the lower-right and upper-left quadrant correspond to *negative* spatial autocorrelation i.e. different values at neighboring locations, and are referred to as *high-low* and *low-high* spatial autocorrelation. Local Indicators of Spatial Association (LISA) maps were also created for all the three diseases to identify specific wards contributing towards positive and negative spatial autocorrelation.

Spatial Regression Models for disease dynamics

Ordinary Least Square (OLS) and Spatial Lag Regression (SLR) models were fitted using the *spdep* package of R studio version 3.3.3 to detect the risk factors associated with the disease risk. The OLS is a simple linear regression model. While in the SLR model, the dependent variable in place i is affected by independent variables in both places i and j (refer Eq. 1).

The model performance between the OLS and SLR models was examined based on Akaike Information Criterion (AIC) values. Moran's I plots for residuals were also checked to determine the presence of spatial dependence and heteroscedasticity in the residuals of each model. Models were considered unstable if residuals showed the presence of spatial dependence²¹.

Excess risk mapping associated with risk factors

The Excess Risk Maps (ERM) of each disease were generated using GeoDa 1.80 version. The ERM functionality of GeoDa allows computation of the expected number of events for each ward based on the reference rate for the city and the covariate variable for each ward²². Compared to the overall average incidence maps, the ERM maps simultaneously identify disease incidence and risk factors at a particular place. The excess risk is the ratio of the observed rate to the average rate computed for all the data. This ratio shows which wards have a higher than expected incidence, referred to as *hotspots*, and which wards have lower than expected incidence referred to as *coldspots*. We plotted excess risk maps for all the three diseases with base covariates, significant predictors from regression results were considered for risk mapping.

Results

A total of 32,590, 11,339, and 53,242 cases were reported of viral hepatitis, typhoid, and diarrhea, respectively, during the study period from 2010 to 2017. Table 1 provides the details of the socio-demographic profile of the city. The temporal trend of the diseases showed the cases of diarrhea continued to rise over the study period. In comparison, typhoid and viral hepatitis showed a similar trend with a steep rise of cases in 2011 (Supplementary Fig. 1). Interestingly, all three water-borne infectious diseases reported similar spatial distribution of disease incidence in the city, as shown in Fig. 2. The disease mapping showed higher disease incidence in the eastern part of the city and near the vicinity of the river Sabarmati, mostly concentrated in the southern and central zones of the city. A consistent lower

incidence rate of all three diseases in the west and northwest zones of the city was observed. The stability of the spatial pattern of disease incidence across the wards reflects the strength of the underlying determinants. The high-risk wards are characterized by a higher proportion of slum population, illiterate population, and under six years' population. The distribution maps of these explanatory vulnerability variables are shown in Supplementary Fig. 2.

Table 1
The socio-demographic profile of Ahmedabad city as per 2011 census and cases of water-food-borne infectious diseases

Study Characteristics	Ahmedabad city profile
No. of reported cases (2010–2017)	
Viral Hepatitis	32,590
Typhoid	11,339
Diarrhea	53,242
Socio-demographic variables (as per 2011 census)	
Total Population	5,898,893
Slum Population	798,206
Area (sq. km)	466
Population density (per sq. km)	12,720
Female Population	2,269,306
Male Population	2,521,418
Illiterate Population	1,044,338
Population 0–6 years	533,370

[FIGURE 2]

Spatial autocorrelation analysis of the three diseases in the wards using Moran's I statistics was conducted, as shown in Table 2. All three diseases showed a significant positive spatial autocorrelation, i.e., similar values at neighboring locations. The reported Moran's I statistics ranged from 0.09 for typhoid to 0.21 for diarrhea, all statistically significant at a 0.05 significance level. The highest spatial correlation was observed for diarrhea incidence, indicating tendencies of nearby wards to have a similar prevalence. Supplementary Fig. 3 depicts disease-specific Moran's I scatter plot for the classification of disease clusters. Since most wards clustered in the upper right and lower left quadrant, this indicated positive spatial autocorrelation among wards for the three diseases. Few of the wards also showed negative spatial autocorrelation of diseases.

Table 2
Spatial autocorrelation analysis of diseases using Moran's I statistics

Values	Viral Hepatitis	Typhoid	Diarrhea
Moran's I	0.143*	0.092*	0.212*
Expected	-0.021	-0.021	-0.021
P-value	0.002	0.009*	0.001
Z-value	4.224	3.040	5.233
Standard deviation	0.038	0.037	0.045
* p-values significant at 0.05 level			

The LISA maps of all three diseases, as illustrated in Fig. 3, identified wards that are significantly contributing to positive spatial autocorrelation. Strongly colored regions i.e., red and blue regions represent positive spatial autocorrelation, while pale-colored regions i.e. purple and pink, represent negative spatial autocorrelations. Higher wards contribute to positive spatial autocorrelation compared to negative spatial autocorrelation. The grey-colored wards depict wards with no significant positive or negative autocorrelation contribution. The LISA mapping of diseases indicated incidence in specific wards is a function of disease incidence in neighboring wards.

[FIGURE 3]

We evaluated the dependence of disease incidence over explanatory variables using the univariate non-spatial OLS and SLR models. A comparison of AIC values of OLS and SLR model showed that SLR is a better fit for data than OLS. The results revealed significant positive dependence of viral hepatitis, typhoid, and diarrhea incidence over slum population density and illiteracy, as shown in Table 3. Interestingly, viral hepatitis showed an inverse relationship with the distance of wards from the rivers. As the distance of wards from the river increased (in km.) the disease incidence decreased.

Table 3
Univariate analysis of diseases based on socio-demographic information using Ordinary Least Square (OLS) and Spatial Lag Regression (SLR) models

Incidence rate	Variables	OLS Model		SLR Model	
		Coefficients	AIC	Coefficients	AIC
Viral Hepatitis	Slum population density	0.02*	798.59	0.02*	796.33
	Distance from river (km.)	-0.15*	802.64	-0.13*	801.57
	Illiteracy (%)	70.23*	801.94	61.49*	800.62
	Male (%)	-57.42	806.14	-54.97	803.83
	Female (%)	22.53	807.49	6.06	805.39
	0–6 years population (per 100,000)	0.14	803.89	0.12	802.46
Typhoid	Slum population density	0.01*	690.44	0.01*	692.16
	Distance from river (km.)	0.00	701.26	0.00	701.13
	Illiteracy (%)	21.90*	696.18	19.79*	696.93
	Male (%)	-2.93	701.23	-2.23	701.14
	Female (%)	-1.20	701.26	2.44	701.14
	0–6 years population (per 100,000)	0.04	698.04	0.04	698.10
Diarrhea	Slum population density	0.03*	816.38	0.03*	813.62
	Distance from river (km.)	0.02	827.72	-0.03	821.79
	Illiteracy (%)	106.37*	818.84	86.44*	815.17
	Male (%)	-39.60	827.31	-36.00	821.46
	Female (%)	-31.44	827.54	-15.08	821.88
	0–6 years population (per 100,000)	0.20*	822.94	0.15	818.91
* p-values significant at 0.05 level					

In contrast to the SLR model, the OLS model of diarrhea incidence showed a significant positive association with 0–6 years population (per 100,000). This implies that neighboring wards have no effect on diarrhea incidence based on the childhood population. Gender had no effect on disease incidence for all three diseases.

The significant variables from univariate models were further investigated in multivariate models, as shown in Table 4. Slum population density and illiteracy retained their significance with the incidence rate of viral hepatitis and typhoid in multivariate models. While for diarrhea, only slum population density was identified as a significant factor. For viral hepatitis, the distance from the river has remained a significant risk factor. The comparison of OLS and SLR models based on AIC values showed SLR as a better fit; therefore, the results of the SLR model are considered for further disease risk maps.

Table 4
Multivariate analysis of diseases based on socio-demographic information using Ordinary Least Square (OLS) and Spatial Lag Regression (SLR) models

		OLS Model		SLR Model	
Incidence rate	Variables	Coefficients	AIC	Coefficients	AIC
Viral Hepatitis	Slum population density	0.02*	791.87	0.02*	791.77
	Distance from river (km.)	-0.14*		-0.12*	
	Illiteracy (%)	60.27*		54.00*	
Typhoid	Slum population density	0.01*	689.92	0.01*	687.90
	Illiteracy (%)	18.61*		18.36*	
Diarrhea	Slum population density	0.03*	811.60	0.03*	810.53
	Illiteracy (%)	103.02		97.98	
	0–6 years' population	-0.03		-0.05	
	(per 100,000)				
* p-values significant at 0.05 level					

Finally, the excess risks of all three diseases were mapped based on significant variables as base covariates for a dynamic perspective, as shown in **figure 4**. For viral hepatitis, the study identified five, one, and six wards as high-risk or *hotspots* using slum population density, illiterate population, and distance from the river, respectively, as the base covariates. In addition, the five identified wards based on slum population density also correspond to a higher illiterate population (**Supplementary figure 2**). Slum population density and illiterate population as base covariates identified five wards and one ward respectively at higher risk of typhoid. For diarrhea, six wards were identified as *hotspots* using slum population density as the base covariate. The excess risk analysis of diseases revealed clustering of *hotspots* towards southern and central zones of the city. In contrast, clustering of *coldspots* was seen in the western part of the city or new city. Remarkably, most of the hotspots of the diseases are identified in the wards with proximity to the river indicating the river as a natural marker of disease incidence.

[FIGURE 4]

Discussion

Our study has established a clear association between the distribution of incidence of viral hepatitis, typhoid, and diarrhea and socio-demographic variables in the wards of Ahmedabad city. The spatial heterogeneity of slum population density and illiteracy influence the risk of infections at local scales. Initial disease mapping of the three diseases identified clustering of disease incidence in the wards located to the east of river Sabarmati with a higher incidence in the southern wards. Urbanization is changing the infectious disease risk patterns²³, with differential access of resources leading to variable transmission intensity of infectious diseases²⁴. Therefore, the spatial mapping approach adopted in this study is crucial to delineate the disease prevalence in association with socio-demographical distribution in urban areas.

We found spatial heterogeneity in disease incidence with clustering in the city's eastern part. The presence of differential risk in eastern and western parts of the city could result from differential availability of resources. The eastern part accommodates the old city, while the western part accommodates the new city²⁵. The eastern part of the city includes low-income residential areas predominantly, while the western part consists of middle and upper-middle-income residential areas²⁶. The differences between the disease incidence in the eastern and western parts of the city establish the possibility of differential access to services and infrastructure. Moreover, the spatial mapping of socio-demographic variables also indicated a higher proportion of illiterate population and slum density in the older part of the city (Supplementary Fig. 2). However, it can also be due to a systematic difference in reporting; populations from low-income residential areas tend to visit government healthcare services more often than middle and upper-middle-income groups. Hence these areas have better passive disease reporting.

The slum level comparison identified differential risk patterns of diseases in the eastern and southern zones of the city, which can be due to the process of slum resettlements and disintegration in the city. A study from Ahmedabad reported many *chawls* disintegrated into slums due to poor employment opportunities for the communities in the eastern zones of the city¹⁹. Further, the eastern and southern zones of the city accommodate a higher number of mills and factories, possibly leading to higher informal settlements of slum dwellers in those areas²⁷. Hence, explaining higher clustering of cases towards eastern and southern zones compared to western.

In general, poor civic amenities and aging infrastructure like old water pipes, buildings, drainage systems, etc., lead to higher transmission of diseases^{28,29}. At more local scales, the transmission intensity of the diseases varies due to the massive pressure of providing equal infrastructure, sanitation, and civic amenities³⁰. Poor hygiene, sanitation, and inadequate access to safe drinking water in congested spaces of cities lead to a higher burden of infectious diseases^{31–35}. It is common to have informal water connections in informal settlements of cities, leading to a higher probability of mixing drinking and sewage water, resulting in a perfect breeding ground for water-borne pathogens. Another crucial aspect of

pathogen transmission is intermittent piped water delivery, increasing unsafe water consumption due to longer household water storage in slum areas. The disruption of the continuous water supply in Kolkata, India, urban landscape showed a significant association with water-borne illnesses (typhoid, diarrhea, and hepatitis)³⁶.

The vulnerability of slum populations to diseases is further elevated by illiteracy and higher childbirth rates. Our study captures the spatial heterogeneity of diarrhea incidence associated with the variation in proportions of the childhood population, but not for typhoid and viral hepatitis. There is empirical evidence of diarrhea disease being closely associated with childhood due to higher exposure and transmission of pathogens^{37–39}. Other studies have shown that illiteracy, socio-economic status, and sanitation significantly impact the distribution of under-five diarrhea across India^{15,40}. One study from Ahmednagar district in western Maharashtra, India, showed that low socio-economic status and poor sanitary conditions are responsible for recurrent diarrhea among children⁴¹.

Furthermore, our study also identified a higher sensitivity of viral hepatitis to distance from the river than typhoid and diarrhea. A study by Haas et al. explained that the risk of infection is 10,000 fold greater for virus-contaminated water than for pathogenic bacteria at similar exposures⁴², explaining a higher incidence of viral hepatitis in proximity to the river.

Urban resettlement efforts in the city of Ahmedabad have been recorded since the 1960s⁴³. The resettlement efforts of late 1990s and early 2000s benefitted over 14,000 households with a cost of these services accounting for INR 56,000 (US\$ 1057) per household as per 2011-12 price⁴⁴. But, despite large expenditures on rehabilitation, granular data regarding the effect of these schemes on health and non-health outcomes have not been systematically collected or studied. An early study from Indore²⁹ and a more recent one from Mumbai⁴⁵, which focused on rehabilitated slums, described the lack of socio-physical liveability of such rehabilitated settlements. They conclude that, due to the inherently complex nature of slums, rehabilitation projects need to address beforehand the possible social and health interactions in such settlements. Our study demonstrates that spatial techniques can be an effective tool for city governments to document and monitor the outcomes of large public expenditures on rehabilitation. Spatial techniques help identify spatial '*hotspots*' at the local level to encourage re-alignment of efforts.

This paper has provided comprehensive insights on the distribution of key infectious diseases in Ahmedabad. Given the importance of water-food-borne infectious diseases in an urban landscape, findings from this study will inform urban public health planning. There are some limitations of our study. For instance, we used population-level information as opposed to individual-level data. Higher-resolution data from neighborhoods would have generated more informative results. As such, we could not perform in-depth analysis, including vaccination status and access to medical care. Our study utilized cases reported to municipal corporations, which are mostly generated through government health centers that commonly cater to poorer populations. The richer populations would have lower burdens of such cases

and use private services, which do report to municipal authorities, albeit incompletely. Although this study establishes the association between socio-demographic variables and considered infectious diseases in Ahmedabad, the other environmental and socio-economic factors that must be mediating this effect directly or indirectly have not been adequately elucidated. Although we have tried to retrieve all ward-level data, socio-demographic information for a few wards could not be incorporated. In addition, the study could not incorporate the impact of local climate variables on diseases due to the non-availability of gridded weather data by each ward. Future studies can evaluate the impact of local climate variables on diseases.

Conclusion

This study presented the spatiotemporal pattern of water and food-borne disease in Ahmedabad. The findings of this study shed light upon the importance of the interplay of socio-demographics in shaping the subtleties of urban infectious diseases. The study identified the slum population as a crucial factor influencing the spatial heterogeneity of the diseases. The convergence of infectious diseases to vulnerable populations can stretch the resources of the already strained health system. Therefore, this study recommends localizing improvements in resource allocation through micro-planning and advocating demand-based service deliveries to the slum population. Integrating public health services with urban planning for vulnerable populations by strengthening social protections is a crucial recommendation. Priority should be given to re-aligning efforts to identify local hotspots in urban landscapes and targeting them effectively to reduce the disease burden.

Declarations

Ethics approval and consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and materials: Data not available due to [ethical/legal/commercial] restrictions

Conflict of interest: The authors declare no conflict of interest.

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Author's Contribution

A.S., Y.C.W., and VI: Conceptualization; B.S. and V.I.: Data curation; Y.C.W. and A.Sp.: Funding acquisition; A.Sp., B.S.S.W. and G.A: Formal analysis; A.S., and Y.C.W. : Writing - Original Draft; A.S., A.Sp., L.H.H., V.I., and Y.C.W.: Writing – Review & Editing

All authors read and approved the final version of the manuscript.

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Figures

Figure 1

The map showing administrative boundaries of wards and zones of Ahmedabad city, Gujarat, India

Figure 2

Disease maps of water-food-borne infectious diseases from 2010-2017 in the city of Ahmedabad: Spatial distribution of case rates of (a) Viral Hepatitis, (b) Typhoid, and (c) Diarrhea. The map depicts very similar geographical variability in distribution of all three illnesses, by the intensity of the color, darker brown corresponding to higher case numbers per lakh population (pale yellow to brown).

Figure 3

Maps of Local Indicators of Spatial Association (LISA) of water-food-borne infectious diseases in the city of Ahmedabad: (a) Viral Hepatitis, (b) Typhoid, and (c) Diarrhea

Figure 4

Excess risk maps of water-food-borne infectious diseases with socio-demographic variables as base covariates (a) Viral Hepatitis, (b) Typhoid, and (c) Diarrhea. The map depicts the hotspots (red color) and cold spots (blue color) in the city. The Black color depicts the missing ward data and the numbers in the brackets correspond to the number of wards in each category.

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