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Original Article

Spatial mapping of acute diarrheal disease using GIS and estimation of relative risk using empirical Bayes approach

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ABSTRACT

Background/objectives: Diarrheal disease is one among the top five causes of death in low- and middle-income countries. It is the second leading cause of death in children under five years of age. Diarrheal disease contributes to the mortality of nearly 1.5 million children and globally there are about two billion cases of diarrheal diseases every year. In the present study, we studied the spatio-temporal pattern of acute diarrheal disease (ADD) ward-wise and to estimate and compare two widely used Bayesian models in the study of measuring relative risk of ADD in Chennai Corporation, Tamilnadu, India.

Materials and methods: Data on ADD were obtained from Communicable disease hospital, Chennai, Tamilnadu, India from 2009–11. Geographical Information System (GIS) technique was used to map ADD data ward-wise and relative risk was estimated using empirical Bayes approach using Poisson gamma and Poisson log normal models.

Results: Over a period of three years from 2009–11, nearly 7661 cases of ADD were reported in Chennai Corporation. The cumulative incidence rate of diarrhea was 142.6 cases per 100,000 population ranging from minimum of 0 to maximum of 1699.7 cases per year. Males had higher average incidence 147.4 cases than females with 137.7 cases per 100,000 population per year. Also, the cumulative incidence was higher in the age group of 0–4 years (306.8 cases) than that in any other category. Higher incidence was observed during the months of Apr–Jun (55.2 cases) than that in any other seasons. Choropleth map indicates that higher incidence of ADD was more prevailed in northern part of Chennai near coastal area which includes the wards from Tondiarpet, Basin bridge, and Pulianthope zones. The posterior relative risk estimate obtained using empirical Bayes approach identified 23, 30, and 19 wards having relative risk significantly greater than 1 for years 2009, 2010, and 2011, respectively. Fitting standardized morbidity ratio (SMR) and the other two models showed that, consistently Tondiarpet ward had the highest relative risk of ADD in all the three years (relative risk (95% credible interval) based on SMR, Poisson gamma and Poisson log normal

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models were 13.3 (11.6, 15.2), 13.0 (11.3, 14.8), 13.3 (11.5, 15.1) in 2009 and 8.0 (6.9, 9.2), 7.8 (6.7, 8.9), 8.0 (6.9, 9.1) in 2010 and 19.6 (17.0, 22.3), 19.0 (16.5, 21.7), 19.5 (16.9, 22.1) in 2011, respectively.

Conclusion: GIS mapping of ADD during the years from 2009–11 identified wards having higher incidence near northern part of Chennai near coastal area. Thus estimation of relative risk using empirical Bayes approach and mapping of disease would help us to estimate accurate incidence despite small observations and to take precautionary measure to prevent and control the spread of the disease.

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1. Introduction

The study of infectious diseases helps to understand the origin of the disease, its evolution over time, the role of place and space in the development of the disease and the extent of its spread. Predicting the course and geographic spread of an infectious disease is critical as the cause of the disease is multifactorial, which requires strong mathematical modeling and empirical investigations of infectious diseases.¹ Disease mapping involves visual representation of more complex geographical data, which would help us to generate various hypotheses about etiology, identifying high-risk areas for public health surveillance, and to aid policy making and utility of resources. They are also helpful in identifying disease clusters of specific group.²

Diarrheal disease is one among the top five causes of death in low- and middle-income countries. It is the second leading cause of death in children under five years of age.³ This disease mainly affects children under two year's age. According to UNICEF India report,⁴ 25% of all children under-five years of age died of diarrhea and India ranks first in reporting the highest number of diarrheal deaths among children under five years of age globally. Diarrheal disease kills nearly 1.5 million children and globally there are about two billion cases of diarrheal diseases every year.³ Diarrheal disease is caused because of insecure drinking water and poor sanitation. Open defecation is the main cause of diarrheal disease, which leads to contamination of drinking water owing to transportation of pathogens from human and animal fecal material into drinking water sources during rainy season. Diarrhea and lack of sanitation are the major leading causes of malnutrition among children under five years of age. Incidence of diarrhea could significantly drop, only when open defecation is completely eliminated. Diarrheal disease is both preventable and treatable through economic development, public health measures, and good hygienic practices. Over a period of three years from 2009–11, nearly 7661 cases of acute diarrheal disease (ADD) data were reported in Chennai, Tamilnadu. Other environmental factors such as maximum temperature, total rainfall, relative humidity, and wind speed could contribute to the source and the spread of the infection.

The important application of disease mapping was seen in the analysis of cancer research,⁵ spread of HIV infection,⁶ cholera disease,⁷ etc. Emch and Ali⁸ studied the spatial and temporal patterns of diarrheal disease in Bangladesh. Ali et al.⁹ presented the application of Poisson kriging to the spatial

interpolation of local disease rates of cholera and dysentery data collected in a cholera endemic area (Matlab) of Bangladesh. These findings revealed that the clustering of dysentery was within the range of 1.1 km while this was 0.37 km for cholera; therefore, this observation indicates that cholera was closely clustered in contrast to dysentery. However, these analyses provided larger variance due to weaker spatial clustering of both diseases. Jepsen et al.¹⁰ analyzed *Campylobacter* cases and patients with general diarrhea for clustering in space and time for the large Danish island of Funen during the period 1995–2004, under the assumption that infections caused by 'environmental' factors may show persistent clustering while food borne infections will occur randomly in space. They have shown that a persistent cluster of *Campylobacter* features in the North-Western part of the study area, partly overlapping with a cluster of diarrhea features. These findings might indicate an environmental cause of campylobacteriosis in the area. Chaikaew et al.¹¹ studied the spatial clustering and hotspots of diarrhea in Chiang Mai province in Thailand. The hotspot maps showed spatial trend patterns of diarrhea diffusion. Villages in the middle and northern regions revealed higher incidences. Also, the spatial patterns of diarrhea during the years 2001 and 2006 were found to represent spatially clustered patterns, both at global and local scales. A similar study was also conducted in 2014 in Phayao Province, Thailand to study the spatial pattern of diarrhea incidence.¹²

Standardized morbidity ratio (SMR) has been a widely used measure in disease mapping. Maps of standardized rates and maps of statistical significance are the commonly used approaches in disease mapping. It has the advantage of providing estimates of the parameters of interest (disease rates). Since estimation of SMR was affected by small population size, smoothed rates were recommended. Smoothing or shrinkage relates to the idea of improving the estimate by combining it with other information's. This is done by borrowing strength across observations to estimate the parameter, which in turn improves each observation,¹³ that is using "Empirical Bayes" method. This methodology involves the Bayesian principle, where the posterior distribution of the outcome is described by combining the prior information and likelihood of the observed data. The main objective of this paper is to study the spatio-temporal pattern of ADD in Chennai, Tamilnadu using Geographical Information System (GIS) tool and also to estimate and compare the relative risk estimates obtained using empirical Bayes approach using Poisson gamma and Poisson log normal models.

2. Materials and methods

2.1. Definition of diarrhea

According to WHO, diarrhea is defined as “the passage of 3 or more loose or liquid stools per day, or more frequently than is normal for the individual”.³ This can be caused by bacteria, virus, and parasitic organisms. This is a common indication of gastrointestinal infection.

2.2. ADD data

The data for this study on ADD reported from 2009 to 2011 were obtained from Communicable Diseases Hospital, Chennai, Tamilnadu, India, which is the data coordination center. The reported data contain only the case history of the patients. The variables considered from the above data were sex, age group with eight categories in years (0–4; 5–9; 10–19; 20–29; 30–39; 40–49; 50–59; ≥60). The data regarding environmental variables such as maximum temperature (in Degree Celsius), relative humidity (in percentage), total rainfall (in millimeters), wind speed (in kmph) were obtained from the Regional Meteorological Department, Chennai. Chennai Corporation consists of 155 wards till the year 2010. Chennai ward level spatial layer was obtained from TTK maps Pvt. Ltd. The total population in each of the wards was projected for year's 2009 to 2011 using arithmetic progression method with 2001 as the base population with 7.77% increase from 2001 to 2011. Since the age wise distribution of population total was not available at ward level, we applied the Corporation level age distribution to all the wards. Monthly data were split into four quarters to bring out the effect of various seasons. The study was approved by the Institutional Review Boards at the Christian Medical College, Vellore, India, IRB.Min.No.7108 dated 10.03.2010.

3. Statistical methods

3.1. Choropleth map

Choropleth map was used to visualize the spatial distribution of ADD data. Areas within a region of interest are shaded according to a discrete scale based on the recorded value of the attribute of interest for that area.

3.2. Standardized morbidity ratio

Acute diarrhea disease data were a kind of aggregated data (i.e., count of cases), which are usually being used in disease mapping. The SMR or standardized incidence ratio (SIR) is a common measure of relative risk estimate used in disease mapping. It is defined as the ratio of the observed count to the expected count. Let θ_i be considered as unknown relative risk for ward i with probability density function $f(\theta_i)$. Given that O_i is the observed number of diarrhea cases and E_i is the expected number of diarrhea cases for ward i , standard maximum likelihood estimate (MLE) of θ_i under Poisson assumption is given by $SMR = O_i/E_i$. The aggregated count of

cases of acute diarrhea were categorized into quartiles (or tertiles, etc.) and the regions having values/rates between any two successive quartiles are given a shade of color or pattern of design. Then a map is drawn representing the shades and these maps are interpreted visually. However, this measure depends on the population size of the area. Hence, an area with lower observed counts of cases with low expected number of cases due to small population size can be misleading and classified as high-risk area. To reduce the amount of variation due to population size, empirical Bayes smoothing techniques were applied.

3.3. Empirical Bayes smoothing

The main objective in disease mapping was to estimate and map the unknown underlying risk θ_i for each ward using the information available on the observed number of cases. Empirical Bayes is one of the commonly used smoothing techniques to obtain reliable estimate. In this approach, the estimation of underlying risks would be obtained by making the assumption of nature of the prior distribution. The prior distribution has to be completely specified in the fully Bayesian approach whereas in the empirical Bayes approach assumption about the prior distribution was only needed. The parameters of the prior distribution were obtained empirically from the observed data.^{13,14} The posterior distribution was obtained by combining the Poisson likelihood with the prior distribution. This results in distribution of possible values of the underlying risks of the wards conditional upon the observed number of cases. The empirical Bayes estimate of the true risk would be taken as the mean of posterior distribution. In the analysis of spatial diarrhea data, we used gamma and log-normal priors. Poisson distribution as likelihood mixed with gamma distribution as prior would produce Negative binomial distribution as posterior distribution.^{15–19}

3.4. Empirical Bayes estimation of relative risks for ADD

In the estimation of relative risk using empirical Bayes method, let O_{ij} be the observed number of diarrhea cases and N_{ij} be the population size in the i th ward for the j th age group ($i = 1, 2, \dots, 155$; $j = 1, 2, \dots, 8$), respectively. Using the multiplicative model we define $\hat{O}_{ij} = \theta_i \xi_j N_{ij}$, where θ_i is the effect due to the i th ward and ξ_j is the effect due to j th age group. In this analysis we used 8 age groups to determine the expected counts $\xi_j N_{ij}$. Our interest here is the estimation of θ_i , the relative risk for the i th ward. Hence the SMR is defined as $\hat{\theta}_i = \hat{O}_i/E_i$ where $O_i = \sum_{j=1}^8 O_{ij}$ is the observed number of diarrhea case for ward i and $E_i = \sum_{j=1}^8 \xi_j N_{ij}$ is the expected number of diarrhea case in ward i ($i = 1, 2, \dots, 155$). Conditional on θ_i , the O_i 's was assumed to be independent Poisson random variable with $E(O_i|\theta_i) = E_i\theta_i$. Suppose that θ_i has prior density function $f(\theta_i)$ with $E_\theta(\theta_i) = \mu_i$ and $Var_\theta(\theta_i) = \sigma_i^2$ under the squared error loss function, the best linear Bayes estimator of θ_i is given by $\hat{\theta}_i^B = (1-B_i)\hat{\theta}_i + B_i\mu_i$ where $B_i = \mu_i/(E_i\sigma_i^2 + \mu_i)$ for $i = 1, 2, \dots, 155$. The unknown μ_i and σ_i^2 in the above empirical Bayes estimate is replaced by their estimates $\hat{\mu}_i$ and $\hat{\sigma}_i^2$ and is given by $\hat{\theta}_i^{EB} = (1-\hat{B}_i)\hat{\theta}_i + \hat{B}_i\hat{\mu}_i$, where $\hat{B}_i = \hat{\mu}_i/(E_i\hat{\sigma}_i^2 + \hat{\mu}_i)$ for $i = 1, 2, \dots, 155$.²⁰

3.5. Gamma prior model

In the estimation of θ_i , the relative risk estimate for the i th ward, we assume a priori that θ_i 's are distributed as gamma random variables with shape parameter α and scale parameter β . That is $E(\theta_i) = \alpha/\beta = \mu$ and $\text{Var}(\theta_i) = \alpha/\beta^2 = \sigma^2$. The advantage of using gamma prior model for estimating θ_i here is the reduction from 2×155 ($\mu_1, \dots, \mu_{155}, \sigma_1^2, \dots, \sigma_{155}^2$) parameters to two parameters μ and σ^2 . Here, conditional on θ_i 's, the O_i 's are independent Poisson random variables with means $E_i\theta_i$ ($i = 1, 2, \dots, 155$). Under the squared error loss function and the gamma model, the Bayes estimator of θ_i is given by $\hat{\theta}_i^B = (O_i + \alpha)/(E_i + \beta) = (1 - B_i)\hat{\theta}_i + B_i\mu$, where $B_i = \beta/(E_i + \beta)$ for $i = 1, 2, \dots, 155$. Usually α and β are unknown and would be replaced by their estimates $\hat{\alpha}$ and $\hat{\beta}$ resulting in the empirical Bayes estimate $\hat{\theta}_i^{EB} = (1 - \hat{B}_i)\hat{\theta}_i + \hat{B}_i\hat{\mu}$ where $\hat{B}_i = \hat{\beta}/(E_i + \hat{\beta})$ for $i = 1, 2, \dots, 155$ and $\hat{\mu} = \hat{\alpha}/\hat{\beta}$.²⁰

3.6. Log-normal prior model

Secondly, we assumed that the θ_i 's were distributed as log normal random variable with $\xi_i = \log(\theta_i)$ so that ξ_i 's follows identically and independently distributed normal random variable with mean μ and variance σ^2 . Generally in log-normal model, the empirical Bayes estimate $E(\theta_i|O_i)$ does not have a closed form, and will only be approximated. Clayton and Kaldor¹⁵ considered the bias-corrected version of $\hat{\xi}_i = \log[(O_i + 0.5)/E_i]$ instead of $\xi_i = \log(O_i/E_i)$ as the latter is undefined for $O_i = 0$. Now the empirical Bayes estimator of ξ_i is given by $\hat{\xi}_i^{EB} = (\hat{\mu} + \hat{\sigma}^2(O_i + 0.5)\hat{\xi}_i - 0.5\hat{\sigma}^2)/(1 + \hat{\sigma}^2(O_i + 0.5))$ which can also be written as $\hat{\xi}_i^{EB} = (1 - \hat{\gamma}_i)\hat{\xi}_i + \hat{\gamma}_i\hat{\mu} - 0.5\hat{\gamma}_i\hat{\sigma}^2$ where $\hat{\gamma}_i = [1 + \hat{\sigma}^2(O_i + 0.5)]^{-1}$ so that θ_i can then be estimated as $\exp(\hat{\xi}_i^{EB})$.²⁰

4. Results

Chennai Corporation consists of 10 Zones and 155 Wards till 2010. After mid-2011, Chennai Corporation was expanded to 15

Zones and 200 Wards. The total population of Chennai in 2001 was 4.34 million. There was 7.7% increase in total population from 2001 to 2011 with 4.68 million. The cumulative incidence rate of diarrhea in Chennai was 142.6 cases per 100,000 population ranging from minimum of 0 to maximum of 1699.7 cases per year. Males have higher average incidence rate of 147.4 cases than females with 137.7 cases per 100,000 population per year. The incidence rate of diarrhea by age group, sex, and season for the year 2009–11 and overall is presented in Table 1.

Among the age group 0–4 years category, the cumulative incidence rate was 306.8 cases which is higher than any other age categories of 5–9 years with 70.5 cases, 10–19 years with 73.5 cases, 20–29 years with 113.1 cases, 30–39 years with 136.3 cases, 40–49 years with 182.2 cases, 50–59 years with 205.0 cases, and 60+ years with 196.4 cases per 100,000 population per year, respectively. There is high cumulative incidence rate of 55.2 cases in the month of April to June than compared to other seasonal months, July to September with 44.2 cases, October to December with 25.2 cases and January to March with lowest of 18.1 cases per 100,000 population per year.

Choropleth maps of age standardized incidence rates of Diarrhea for the years 2009 to 2011 are presented in Fig. 1. As an exploratory analysis, choropleth maps of diarrheal incidence rates were also considered for sex and four seasons for three years Fig. 2. A little variation was found in the diarrheal incidence because of gender. There may be variation among the quantity displayed in choropleth maps. Thus the quantities projected in maps are always either age or age-sex standardized. The age-standardized rates were obtained by using internal standards, i.e. Corporation level age specific distribution was applied to these data. The legend used for displaying choropleth maps was wards with no reported diarrhea counts, <150, 150–250, 250–350, >350 cases per 100,000 population. We used manual classification approach to provide the legend. Choropleth maps suggest that extreme incidence of diarrhea cases were from northern part of

Table 1 – Descriptive statistics of diarrheal incidence rates by sex, age, and season for the years 2009–11 and overall.

Variables	2009			2010			2011			Overall		
	Mean	SD	Max.	Mean	SD	Max.	Mean	SD	Max.	Mean	SD	Max.
Overall	44.83	91.96	592.35	69.55	93.52	536.50	29.22	72.32	581.86	142.58	249.34	1699.72
Sex												
Male	45.66	95.16	620.56	74.99	96.79	582.51	27.81	71.45	612.58	147.40	251.49	1804.01
Female	43.94	90.83	562.99	63.91	92.85	488.61	30.83	75.21	549.89	137.71	249.94	1591.17
Age (years)												
0–4	101.89	242.57	1349.60	115.67	208.94	1220.26	91.25	266.79	2220.38	306.77	678.76	4682.99
5–9	24.07	65.65	476.61	32.99	65.39	414.41	13.95	43.20	271.75	70.49	140.92	723.82
10–19	24.61	53.94	325.30	37.57	55.42	291.67	11.88	31.69	213.56	73.50	125.34	793.23
20–29	35.73	70.51	463.93	63.37	78.59	393.08	14.87	38.41	296.33	113.12	171.22	1144.91
30–39	43.94	96.28	635.72	67.69	97.57	614.43	25.66	72.13	593.62	136.29	252.58	1831.73
40–49	55.01	120.75	702.90	92.47	144.48	794.54	36.04	90.93	741.70	182.22	335.99	2225.10
50–59	58.79	126.18	753.23	97.64	152.75	882.07	49.93	106.29	632.00	204.99	359.34	2044.71
≥60	56.76	120.97	822.83	95.99	136.76	700.63	45.00	109.00	861.27	196.42	335.09	2101.51
Seasons												
Jan–Mar	5.44	13.45	87.11	7.00	17.64	123.87	5.74	14.70	111.79	18.07	43.56	315.29
Apr–Jun	14.89	28.61	182.93	32.35	40.28	199.27	8.32	24.02	189.18	55.17	85.86	561.80
Jul–Sep	14.41	31.77	207.82	22.22	29.81	158.64	7.86	17.38	134.72	44.17	72.15	490.14
Oct–Dec	10.06	22.76	129.58	7.98	15.99	77.59	7.30	18.62	146.18	25.16	54.39	332.49

Note: The minimum incidence in all the years was 0, and hence it has been ignored.

Fig. 1 – Choropleth maps of year wise age standardized Incidence rates of diarrhea for 2009 to 2011.

Chennai Corporation. The map of Chennai city clearly showed that northern part of Chennai near to the coastal area which mainly included the wards of Tondiarpet, Basin bridge and Pulianthope zones had the highest incidence of ADD for all years from 2009–11. This could be due to dense population and the breeding places for many pathogens in these areas. The incidence of ADD was relatively lower in the southern part of the Chennai, but still most of the wards had less number of cases of diarrhea. Only very limited wards did not have incidence cases of diarrhea.

Tables 2a–2c presents the relative risks estimates of different wards based on SMR, Empirical Bayes with Poisson gamma and Poisson log normal models along with 95% credible interval (CI). The tables are obtained from observed and age adjusted expected counts of diarrhea for the year 2009–2011. The Wards with relative risks significantly greater than 1 were presented and arranged according to highest order of relative risk by SMR. These wards could be a potential source of spatial clusters of higher rates. The SMR ranged from 1.61 to 13.28 in 2009, 1.54 to 7.99 in 2010 and 1.80 to 19.55 in 2011. The posterior relative risk estimate using Poisson gamma model ranges from 1.60 to 12.97 in 2009, 1.53 to 7.77 in 2010 and 1.77 to 19.00 in 2011. Similar estimates were also observed using Poisson log normal model ranged from 1.58 to 13.25 in 2009, 1.52 to 7.97 in 2010 and 1.67 to 19.45 in 2011 respectively. Consistently, for the year 2009–11, the highest relative risks were observed from the wards (ward no: 14, 5, 3, and 7) of Tondiarpet zone. In 2009, the top three significant wards were: Tondiarpet (ward no: 14, SMR: 13.28 (95% CI: 11.56, 15.20)), Jeeva nagar (North) (ward no: 5, SMR: 11.42 (95% CI: 9.91, 13.03)), Jeeva nagar (South) (ward no: 7, SMR: 8.74 (95% CI: 7.03, 10.66)). Similarly, in 2010 the top three significant wards which had higher risk of diarrhea were Tondiarpet (ward no: 14, SMR: 7.99 (95% CI: 6.89, 9.17)), Jeeva nagar (North) (ward no: 5, SMR: 6.98 (95% CI: 6.03, 8.01)), Dr. Radhakrishnan nagar (North) (ward no: 3, SMR: 6.66 (95% CI: 5.78, 7.56)). Again in 2011, the highest risk was seen in Tondiarpet (ward no: 14, SMR: 19.55 (95% CI: 17.00, 22.30)) then Dr. Radhakrishnan nagar (North) (ward no: 3, SMR: 11.36 (95% CI: 9.64, 13.22)) and the third highest ward was Jeeva

nagar (North) (ward no: 5, SMR: 9.90 (95% CI: 8.19, 11.69)). All these wards were from Tondiarpet Zone, which is near to coastal area of northern part of Chennai. The empirical Bayes rates obtained using Poisson gamma and Poisson log normal models were found to be slightly smoothed as compared to SMR, i.e., all the three methods provided same results with small amount of smoothing due to considerable population in the wards. However, the width of the CI obtained using gamma model was somewhat narrower as compared to log-normal model.

5. Discussion

We mapped ward-wise incidence and the spatial distribution of ADD for each year separately from 2009–11 using GIS techniques. This helps to understand the intensity of disease in different color patterns. We used SMR and Empirical Bayes smoothed estimate obtained using Poisson gamma and Poisson log-normal models to determine the geographical distribution and the spatial variation of incidence of diarrhea per 100,000 population for 155 wards. We produced choropleth maps of age standardized diarrheal incidence rates for years 2009 to 2011 which shows high incidence rates in northern part of Chennai includes Tondiarpet, Basin bridge, and Pulianthope zones. The similar results were also observed in the study of Cholera cases in Chennai city.⁷ ADD which is not only influenced by geographical factor but could also be affected by other parameters including rainfall, temperature, humidity, etc. Hence we also explored the ADD by seasons. In our study in almost all of the seasons the incidences were predominantly more in the coastal area of northern Chennai. And we also observed that, over the three years there was not much change in the incidence of diarrhea. The predominance of diarrheal disease near coastal area could be because of the presence of many pathogens (especially cholera), which lives in the environment in brackish rivers and coastal water and also the presence of higher levels of enteric microorganisms in coastal area. In many epidemiology studies, it was observed

Fig. 2 – Choropleth maps of age standardized Incidence rates of diarrhea among four seasons for 2009 to 2011.

that the people living near to coastal area are at higher risk of contracting diseases. This could be due to the polluted coastal water may run into inland during rainy season leads to higher incidence of diarrhea and its transmission.^{7,21–23} Moreover, alike to our study, the higher incidence of cholera was

observed near the coastal area of Bangladesh.²² We also observed in our study data that the occurrences of diarrheal episodes were high in summer season especially during the month of May. Particularly in the year 2010, the reported number of diarrheal counts was high throughout all the wards.

Table 2a – Relative risk estimates of wards by standardized morbidity ratio (SMR), Empirical Bayes (EB) with Poisson Gamma model and Poisson Log Normal model with 95% credible intervals (CI) for the year 2009.

2009				
Ward no.	Ward name	SMR (95% CI)	EB with Poisson gamma model (95% CI)	EB with Poisson log normal model (95% CI)
14	Tondiarpet	13.28 (11.56, 15.20)	12.97 (11.27, 14.79)	13.25 (11.50, 15.10)
5	Jeeva nagar (north)	11.42 (9.91, 13.03)	11.21 (9.72, 12.81)	11.37 (9.90, 13.01)
7	Jeeva nagar (south)	8.74 (7.03, 10.66)	8.46 (6.81, 10.34)	8.54 (6.90, 10.47)
10	Kumarasamy nagar (south)	8.42 (7.13, 9.75)	8.24 (6.99, 9.59)	8.35 (7.10, 9.67)
3	Dr. Radhakrishnan nagar (north)	7.96 (6.79, 9.20)	7.83 (6.67, 9.13)	7.87 (6.72, 9.16)
8	Korukkupet	6.48 (5.26, 7.83)	6.33 (5.12, 7.64)	6.39 (5.10, 7.80)
13	Vijayaragavalu nagar (west)	6.03 (4.61, 7.70)	5.83 (4.46, 7.42)	5.84 (4.41, 7.51)
6	Cheriyar nagar (south)	5.48 (4.16, 6.94)	5.30 (4.01, 6.78)	5.33 (4.01, 6.83)
11	Dr. Radhakrishnan nagar (south)	5.23 (4.08, 6.53)	5.09 (3.95, 6.39)	5.13 (4.01, 6.41)
12	Kumarasamy nagar (north)	4.99 (3.60, 6.71)	4.81 (3.46, 6.38)	4.81 (3.49, 6.33)
4	Cheriyar nagar (north)	4.98 (3.71, 6.46)	4.82 (3.57, 6.32)	4.87 (3.62, 6.28)
17	Ma-Po-Si-nagar	4.06 (2.98, 5.31)	3.96 (2.90, 5.19)	3.98 (2.92, 5.28)
27	Vallal Seethakathi nagar	3.68 (2.49, 5.05)	3.54 (2.44, 4.85)	3.52 (2.41, 4.83)
32	Vyasarpur (south)	3.39 (2.59, 4.29)	3.33 (2.51, 4.23)	3.32 (2.55, 4.20)
30	Sowcarpet	2.81 (1.76, 4.09)	2.72 (1.74, 3.98)	2.67 (1.60, 3.97)
31	Basin bridge	2.32 (1.53, 3.28)	2.26 (1.53, 3.16)	2.23 (1.45, 3.22)
24	Seven hills (north)	2.22 (1.32, 3.36)	2.15 (1.30, 3.22)	2.10 (1.25, 3.14)
49	Edapalayam	2.13 (1.19, 3.35)	2.07 (1.15, 3.24)	1.99 (1.10, 3.09)
21	Old washermenpet	2.05 (1.23, 3.09)	2.01 (1.23, 2.99)	1.96 (1.17, 2.96)
22	Meenakshiammanpet	2.00 (1.32, 2.81)	1.97 (1.29, 2.78)	1.93 (1.28, 2.74)
40	Dr. Sathayavanimuthu nagar	1.98 (1.40, 2.65)	1.96 (1.38, 2.62)	1.94 (1.38, 2.62)
23	Kondithope	1.93 (1.08, 3.04)	1.90 (1.03, 2.95)	1.82 (1.01, 2.90)
2	Kodungaiyur (east)	1.61 (1.14, 2.16)	1.60 (1.13, 2.14)	1.58 (1.13, 2.12)

Table 2b – Relative risk estimates of wards by standardized morbidity ratio (SMR), Empirical Bayes (EB) with Poisson Gamma model and Poisson Log Normal model with 95% credible intervals (CI) for the year 2010.

2010				
Ward no.	Ward name	SMR (95% CI)	EB with Poisson gamma model (95% CI)	EB with Poisson log normal model (95% CI)
14	Tondiarpet	7.99 (6.89, 9.17)	7.77 (6.67, 8.90)	7.97 (6.91, 9.13)
5	Jeeva nagar (north)	6.98 (6.03, 8.01)	6.83 (5.91, 7.83)	6.95 (5.97, 7.96)
3	Dr. Radhakrishnan nagar (north)	6.66 (5.78, 7.56)	6.52 (5.62, 7.43)	6.59 (5.75, 7.53)
10	Kumarasamy nagar (south)	5.92 (5.05, 6.88)	5.78 (4.93, 6.72)	5.87 (4.98, 6.78)
7	Jeeva nagar (south)	4.90 (3.86, 6.03)	4.71 (3.70, 5.85)	4.80 (3.76, 5.93)
12	Kumarasamy nagar (north)	4.59 (3.47, 5.88)	4.38 (3.30, 5.59)	4.47 (3.44, 5.69)
13	Vijayaragavalu nagar (west)	4.43 (3.42, 5.57)	4.25 (3.29, 5.31)	4.32 (3.32, 5.47)
27	Vallal Seethakathi nagar	3.98 (2.99, 5.07)	3.79 (2.84, 4.93)	3.84 (2.87, 4.92)
32	Vyasarpur (south)	3.92 (3.20, 4.72)	3.84 (3.15, 4.62)	3.86 (3.15, 4.67)
11	Dr. Radhakrishnan nagar (south)	3.54 (2.76, 4.40)	3.43 (2.68, 4.25)	3.46 (2.71, 4.37)
6	Cheriyar nagar (south)	3.27 (2.46, 4.21)	3.19 (2.36, 4.09)	3.19 (2.38, 4.06)
8	Korukkupet	3.11 (2.43, 3.87)	3.04 (2.39, 3.80)	3.06 (2.36, 3.83)
17	Ma-Po-Si-nagar	3.07 (2.28, 3.97)	2.99 (2.22, 3.85)	3.00 (2.27, 3.89)
30	Sowcarpet	2.93 (2.04, 3.99)	2.82 (1.97, 3.78)	2.85 (1.98, 3.90)
40	Dr. Sathayavanimuthu nagar	2.84 (2.27, 3.47)	2.79 (2.23, 3.43)	2.82 (2.26, 3.45)
31	Basin bridge	2.71 (2.00, 3.52)	2.64 (1.93, 3.39)	2.65 (1.96, 3.49)
44	Perumal kovil thottam	2.67 (1.74, 3.79)	2.54 (1.66, 3.60)	2.55 (1.65, 3.62)
4	Cheriyar nagar (north)	2.60 (1.83, 3.49)	2.53 (1.80, 3.37)	2.55 (1.82, 3.41)
49	Edapalayam	2.42 (1.59, 3.42)	2.34 (1.55, 3.31)	2.33 (1.52, 3.32)
42	Dr. Besant nagar	2.31 (1.66, 3.09)	2.27 (1.64, 3.00)	2.28 (1.65, 3.02)
25	Amman kovil	2.29 (1.53, 3.20)	2.22 (1.49, 3.12)	2.21 (1.46, 3.13)
33	Vyasarpur (north)	2.29 (1.74, 2.94)	2.26 (1.72, 2.88)	2.26 (1.71, 2.86)
26	Muthuialpet	2.27 (1.59, 3.05)	2.21 (1.56, 2.98)	2.21 (1.56, 2.94)
41	Pulianthope	2.25 (1.53, 3.12)	2.19 (1.49, 3.03)	2.22 (1.52, 3.05)
28	Kachaleeswarar nagar	2.04 (1.42, 2.76)	2.00 (1.40, 2.69)	1.99 (1.40, 2.70)
39	Wadia nagar	2.02 (1.47, 2.65)	1.99 (1.45, 2.59)	1.96 (1.41, 2.58)
2	Kodungaiyur (east)	1.86 (1.43, 2.34)	1.85 (1.44, 2.31)	1.84 (1.42, 2.30)
79	Adikesavapuram	1.77 (1.21, 2.45)	1.76 (1.21, 2.40)	1.74 (1.20, 2.40)
106	Pudupet	1.57 (1.03, 2.25)	1.55 (0.99, 2.22)	1.50 (0.95, 2.15)
67	Anna nagar (central)	1.54 (1.08, 2.06)	1.53 (1.07, 2.05)	1.52 (1.07, 2.01)

Table 2c – Relative risk estimates of wards by standardized morbidity ratio (SMR), Empirical Bayes (EB) with Poisson Gamma model and Poisson Log Normal model with 95% credible intervals (CI) for the year 2011.

2011				
Ward no.	Ward name	SMR (95% CI)	EB with Poisson gamma model (95% CI)	EB with Poisson log normal model (95% CI)
14	Tondiarpet	19.55 (17.00, 22.30)	19.00 (16.47, 21.72)	19.45 (16.90, 22.14)
3	Dr. Radhakrishnan nagar (north)	11.36 (9.64, 13.22)	11.12 (9.46, 12.89)	11.23 (9.64, 13.05)
5	Jeeva nagar (north)	9.90 (8.19, 11.69)	9.68 (8.07, 11.46)	9.81 (8.15, 11.67)
7	Jeeva nagar (south)	9.36 (7.28, 11.82)	8.96 (6.95, 11.25)	9.06 (7.01, 11.30)
10	Kumarasamy nagar (south)	8.82 (7.24, 10.60)	8.63 (7.09, 10.31)	8.69 (7.17, 10.37)
6	Cheriyar nagar (south)	6.46 (4.70, 8.49)	6.23 (4.57, 8.11)	6.18 (4.55, 8.09)
11	Dr. Radhakrishnan nagar (south)	6.09 (4.57, 7.78)	5.90 (4.44, 7.58)	5.97 (4.47, 7.82)
8	Korukkupet	5.84 (4.43, 7.43)	5.69 (4.36, 7.28)	5.66 (4.23, 7.32)
13	Vijayaragavalu nagar (west)	5.58 (3.93, 7.49)	5.40 (3.79, 7.29)	5.35 (3.76, 7.26)
12	Kumarasamy nagar (north)	5.31 (3.56, 7.41)	5.05 (3.37, 7.03)	5.05 (3.34, 7.05)
4	Cheriyar nagar (north)	5.04 (3.46, 6.90)	4.87 (3.40, 6.66)	4.87 (3.32, 6.65)
27	Vallal Seethakathi nagar	3.29 (1.98, 4.93)	3.16 (1.91, 4.71)	3.05 (1.83, 4.62)
17	Ma-Po-Si-nagar	2.85 (1.80, 4.17)	2.78 (1.76, 4.08)	2.69 (1.69, 3.98)
31	Basin bridge	2.65 (1.65, 3.86)	2.59 (1.64, 3.75)	2.51 (1.55, 3.70)
21	Old washermenpet	2.54 (1.44, 3.94)	2.46 (1.44, 3.77)	2.35 (1.37, 3.71)
32	Vyasarpet (south)	2.52 (1.70, 3.51)	2.47 (1.68, 3.42)	2.42 (1.67, 3.32)
9	Mottai thottam	2.27 (1.24, 3.60)	2.19 (1.22, 3.45)	2.09 (1.15, 3.31)
33	Vyasarpet (north)	2.07 (1.31, 3.00)	2.03 (1.31, 2.94)	1.98 (1.27, 2.89)
22	Meenakshiammanpet	1.80 (1.03, 2.77)	1.77 (1.01, 2.72)	1.67 (0.96, 2.63)

This could be because of highest single data rainfall in May 2010 in Chennai. Chennai received 204 mm rainfall in the month of May in 2010, with more than 109 mm rain recorded in a single day.^{24,25} This resulted in contamination of surface and shallow groundwater after heavy rainfall.

Emch and Ali⁸ studied the spatial and temporal patterns of cholera and noncholera watery diarrhea in Bangladesh. They have reported that there were many small, highly dispersed high-risk areas for cholera. In contrast, the high-risk areas for noncholera are clustered in only a few areas. While this study has brought out the challenges in the spatial analyses due small incidences, however, has not attempted to use appropriate statistical methods such as Empirical Bayes. Therefore, the findings may have been subjected to precision issues. Ali et al.⁹ presented the application of Poisson kriging to the spatial interpolation of local disease rates of cholera and dysentery data collected in a cholera endemic area (Matlab) of Bangladesh. These findings revealed that the clustering of dysentery was within the range of 1.1 km. Thus this study finding had similar findings like our study. However, these analyses provided larger variance due to weaker spatial clustering of both diseases. Therefore, there is a scope to use better methods such as Empirical Bayes to estimate robust variance. Chaikaew et al.¹¹ reported the hot spots of diarrhea in Chiang Mai province of Thailand. Their findings were similar to this study finding that the villages that had higher levels of diarrhea were clustered together, though the study had failed to present the incidence of diarrhea.

In this study, we estimated SMR's for each ward by using ratio of the observed number of diarrhea cases to expected number of diarrhea cases. Expected number of diarrhea cases was calculated by using age adjusted internal standardization. Standardization reduces some amount of variability among the rates. Several authors used this measure to study the spatial distribution of disease rates as an exploratory analysis and addressed the drawbacks of this measure. Standardized

mortality/morbidity ratio was used to study the cause specific mortality due to hepatocellular carcinoma and liver disease,²⁶ to study the suicide mortality time trend in the place of Catalonia and Spain,²⁷ to address the public health problem of gastric cancer and mortality in Para state and Belem city,²⁸ to examine the factors affecting mortality from acute myocardial infarction, to analyze peptic ulcer bleeding data and to study the trends and factors for inflammatory bowel disease recently.

To overcome the problem of small population size, we used empirical Bayesian estimation of relative risk. In this technique the prior distribution of the estimates was empirically evaluated from the observed data and then multiplied with likelihood of the observed data to form the posterior distribution to obtain the estimates of relative risks.¹³ We adopted two prior distributions namely gamma and log-normal with Poisson likelihood for the observed diarrheal incidence data to produce Poisson gamma and Poisson log-normal posterior distributions respectively. Both methods provided comparable estimates of smoothed relative risks than SMR. We observed that the relative risk estimates obtained using Poisson gamma and Poisson log-normal models were almost identical (close enough to each other) that a difference is negligible. One justification for similarities between results of the two models could be related to the considerable population in each of the wards, which resulted in smaller amount of smoothing. Along with point estimates these models also provides CIs obtained using Bayesian approach. It was noted in our study that the width of the CI of Poisson gamma model was a bit narrower than those from Poisson log normal model. Similar to our study findings, it was also observed in many studies that the performance of Poisson gamma and Poisson log-normal models were similar in terms of providing shrinkage.²⁹ Therefore we would suggest Poisson gamma model for spatial clustering. However, this needs to be validated using simulation studies. The CI which does not cover 1 was considered as significant wards with lower or higher relative risks. The

problem in this method was the testing of significance for all wards without taking adjustment for multiplicity. Further studies should emphasize the necessity to test for multiple hypothesis. Many authors used empirical Bayesian approach in the study of spatial and temporal pattern of different disease rates. Similar approaches were applied in literature includes Tsutakawa et al.³⁰ used empirical Bayes approach in estimating the rates of stomach and bladder cancer. Cressie³¹ emphasized small area prediction of incidence rates and applied empirical Bayes to reduce the noise component due to location error and measurement error. Lawson et al.³² compared the relative merits of smoothing technique for the analysis of small area disease incidence rates. Yasui et al.³³ employed different prior distributions like gamma, log-normal and nonparametric in empirical and fully Bayesian estimation of region specific relative risks. Yiannakoulis et al.³⁴ used empirical Bayes estimates of fall incidence rate among the elderly patients. Smoothed mortality suicide rates were obtained using empirical Bayes in Tuscany.³⁵ A comparison of fully Bayesian and empirical Bayes methods was done in estimation of disease rates in spatial temporal variations.³⁶ Rezaeian et al.³⁷ suggested the use of smooth rates in case of instability and used non iterative empirical Bayes method. Empirical Bayes method was used to smooth the rates and to study the spatial pattern of legionellosis in Spain.³⁸ Smoothed empirical Bayes estimates were used to investigate the spatial pattern of the incidence of pulmonary tuberculosis in Victoria, Brazil.³⁹ Similarly empirical Bayes smoothing technique was used to estimate the rates in the study on spatial distribution of childhood tuberculosis, dengue and chlamydia.

The limitations of our study was lack of other covariate information. Information on socio demographic variables and other lifestyle factors such as socio economic status, source of drinking water, toilet facility, and other hygienic practices were not available in hospital records, registries, or other common sources of data. Hence these were not considered in this study. The demographic variables that were considered in our study were taken from 2001 Census with assumption that no major changes had happened.

6. Conclusion

The exploratory spatial analysis of age standardized diarrheal incidence rates using choropleth maps were produced. Wards with high incidence rates were found near the northern part of Chennai Corporation especially wards in Tondiarpet, Basin bridge and Pulianthope zones and lesser incidence was seen in the southern part of Chennai. This higher incidence could be because of closer vicinity to coastal area. The choropleth maps of incidence rates among various seasons also depicted the seasonal variations. The empirical Bayes smoothing of diarrheal incidence rates obtained by using Poisson gamma and Poisson log normal models identified 23, 30, and 19 wards having relative risks significantly greater than 1 for years 2009, 2010, and 2011 respectively. Thus GIS mapping and estimation of relative risk using empirical Bayes approach would help us to estimate accurate incidence despite small observations and to take precautionary measures to prevent and control the spread of the disease.

Ethical approval

This study was approved by the Institutional Review Board of Christian Medical College Vellore, India; IRB.Min.No.7108 dated 10.03.2010.

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Conflicts of interest

The authors have none to declare.

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