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Malaria Prone Zones of West Bengal: A Spatio-Temporal Scenario

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***Abstract*—**In India, till today, malaria is considered to be one of the significant infectious diseases. Most of the cases regional geographical factors are the principal elements to let the places a unique identity. The incidence and intensity of infectious diseases are quite common and affect different places differently across the nation. The present study aims to identify spatial clusters of hot spots and cold spots of malaria incidence and their seasonal variation during the three periods of 2012-2014, 2015-2017 and 2018-20 in the state of West Bengal in India. As malaria is a vector-borne disease, numbers of positive test results are to be reported by the laboratories to the Department of Health, West Bengal (through the National Vector Borne Disease Control Programme). Data on block-wise monthly malaria positive cases are collected from Health Management Information System (HMIS), Ministry of Health and Family Welfare, Government of India. Moran's I statistic is performed to assess the spatial autocorrelation of malaria incidence. The spatial statistical analysis mainly Local Indicators of Spatial Autocorrelation (LISA) cluster and Local Geary Cluster are applied to find the spatial clusters of hot spots and cold spots and seasonal variability of malaria incidence over the three periods. The result indicates that the spatial distribution of malaria is clustered during each of the three periods of 2012-2014, 2015-2017 and 2018-20. The analysis shows that in all the cases, high-high clusters are primarily concentrated in the western (Purulia, Paschim Medinipur districts), central (Maldah, Murshidabad districts) and the northern parts (Jalpaiguri, Kochbihar districts) and low-low clusters are found in the lower Gangetic plain (central-south) mainly and northern parts of West Bengal during the stipulated period. Apart from this seasonal variability inter-year variation is also visible. The results from different methods of this study indicate significant variation in the spatial distribution of malaria incidence in West Bengal and high incidence clusters are primarily persistently concentrated over the western part during 2012-2020 along with a strong seasonal pattern with a peak in rainy and autumn. By applying the different techniques in identifying the different degrees of incidence zones of malaria across West Bengal, some specific pockets or malaria hotspots are marked and identified where the incidence rates are quite harmonious over the different periods. From this analysis, it is clear that malaria is not a disease that is distributed uniformly across the state; some specific pockets are more prone to be affected in particular seasons of each year. Disease ecology and spatial patterns must be the factors in explaining the real factors for the higher incidence of this issue within those affected districts. The further study mainly by applying empirical approach is needed for discerning the strong relationship between communicable disease and other associated affecting factors.

***Keywords*—**Malaria, infectious diseases, spatial statistics, spatial autocorrelation, LISA.

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I. Introduction

MALARIA is an acute infectious fever that is transmitted by mosquitoes. Protozoal disease malaria is developed by female Anopheline mosquitoes due to the transmission of parasites of the genus Plasmodium to humans.

In developing countries, the rate of spread of communicable diseases is still high than in developed countries. These vector-borne diseases are mainly concentrated in Tropical and Subtropical region throughout the World. Geographical location and climate play a crucial role in disease transmission. In India, favorable climatic condition acts as a stimuli factor in malaria transmission. It is a seasonal disease and maximum incidence occurs during monsoon and post-monsoon [1]. It also imposes social and economic burden on humanity along with other diseases [2]. Global Disease Burden report shows that though at present non-communicable diseases are positioned as the principal causes of death, in spite of that few communicable diseases like respiratory infection, diarrhea, tuberculosis, malaria etc. are still present in the environment [3]. According to the World Malaria Report, 2018 released by the World Health Organization (WHO), India, along with 15 countries in sub-Saharan Africa, contribute about 80% of the global burden of malaria [4]. The report is in tune with the recent findings by the Indian Council of Medical Research (ICMR), which observed that there has been a gradual shift of the parasite burden from *Plasmodium vivax* to *Plasmodium falciparum* [5]. The WHO report has highlighted that about 82% of estimated vivax malaria cases in 2017 were reported from just five countries—India, Pakistan, Ethiopia, Afghanistan and Indonesia. However, *Plasmodium falciparum* is also significantly contributing to the disease burden [4].

The present work is an attempt to find out the spatial clusters of hot spots and cold spots of malaria incidence and their seasonal variation during the three periods of 2012-2014, 2015-2017 and 2018-20 in the state of West Bengal in India using Geographic Information System (GIS) tools [6], [7].

II. Materials

A. Study Area

West Bengal is located in the eastern part of India between latitudes of 21° 31'-27° 14' N and longitudes of 85° 49'- 89° 51' E. According to the Census 2011, it is the fourth most populous state which occupies 88752 sq. km (34263 sq. mile) with 91 million inhabitants [7]. This Indian state has a significant variation in climate due to its north-south extension. Where the western part faces mainly hot and dry seasons, the northern part experiences wet and cold. Belonging to monsoon climatic region Bengal faces summer, winter and rainy season most significantly. According to the census 2011, West Bengal is divided into 341 blocks. All 341 blocks are chosen for the block level study [7].

B. Data

The National Vector Borne Disease Control Programme (NVBDCP) oversees the prevention and control of six major vector-borne diseases, including malaria, as an umbrella programme under National Health Policy 2002 [9]. This programme monitors block, district, and state data reported by aggregating the total number of cases from Primary Health Centre (PHC) for each month. In West Bengal, Plasmodium vivax and Plasmodium falciparum are the most common causes of malaria. The HMIS division of the Ministry of Health and Family Affairs of India issues a monthly block level report. For this research, a dataset comprising counts of confirmed cases of malaria fever at the block level in West Bengal is gathered, particularly for the two species Plasmodium Vivax and Plasmodium Falciparum [10]. Relevant population data are collected from the Census of India [8].

III. Methods

A. Exploratory Spatial Data Analysis

First, exploratory spatial data analysis is applied to demask spatial patterns. To start off, spatial autocorrelation and local cluster mapping are explored using the global 'Moran's *I*' and 'local Geary' spatial statistical techniques [11], [12]. In this context "global" refers to testing for spatial autocorrelation for the entire study area at once and deriving a single value indicating whether spatial autocorrelation exists and what its strength is.

B. Spatial Autocorrelation (Moran's I)

Moran's *I* spatial autocorrelation statistic is calculated to identify the spatial cluster of malaria fever during three different periods of 2012-2014, 2015-2017 and 2018-20. Moran's *I* is a widely used measure of global spatial autocorrelation, which tests whether there are some relationships between location and attribute values. It is initially suggested by Moran (1948), and popularized through the classic work on spatial autocorrelation by Cliff and Ord (1973) [12], [13]. A significant positive statistic indicates that nearby locations of similar attribute values are more spatially clustered than randomly distributed. In contrast, a significant negative statistic shows dissimilar values at nearby locations showing a more dispersed pattern. The value of Moran's *I* ranges between +1 to -1, where a value close to 0 indicates spatial randomness and a positive and negative value indicates a positive and negative autocorrelation respectively [8], [9]. Moran's *I* statistic:

$$I = \frac{\Sigma_i \Sigma_j w_{ij} z_i \cdot z_j / s_0}{\Sigma_i z_i^2 / n}$$

with ω_{ij} as the elements of the spatial weight matrix, $s_0 = \Sigma_i \Sigma_j w_{ij}$ as the sum of all the weights, and n as the number of observations.

The location of malaria fever cases is Geocoded to the block level digital base map using Arc Map 10.8.1. A distance-based spatial weight matrix using Arc Distance band (where blocks that considers its neighbor up to 31 km distance) is constructed for each pair of blocks using GeoDa [12].

C. Local Indicators of Spatial Association

LISA is used to identify spatial clusters and spatial outliers [9]. There is a relation between Moran scatter plot and cluster map which provides a classification of spatial association into four different classes within four quadrants where high-high and low-low groups are known as spatial clusters and high-low and low-high groups as spatial outliers. High-high refers to blocks with high incidence that are surrounded by neighboring blocks with high incidence and low-low refers to blocks with low incidence that are surrounded by neighboring blocks with low incidence which represent positive spatial autocorrelation. High-low refers to the blocks with high incidence that are surrounded by blocks with low incidence and low-high refers to the blocks with low incidence, surrounded by blocks with high incidence indicating negative spatial autocorrelation [14], [15]. A statistical significance of clusters and outliers with $p < 0.05$ are tested with 999 permutations.

D. Local Geary

Luk Anselin first outlined the Local Geary statistic in 1995 to use it as a different measure of LISA. In global counterpart, it focuses on squared differences rather the dissimilarity where small values of the statistics suggest positive spatial autocorrelation and large values for negative spatial autocorrelation [9]. It generates high-high (positive) and low-low (negative) spatial autocorrelation. As the squaring of the differences removes the sign, it is not possible to assess the association between high-low or low-high outliers [12].

Local Geary statistic is

$$LG_i = \sum_j w_{ij} (x_i - x_j)^2$$

IV. Result

A. Descriptive Statistics

The monthly number of malaria cases and monthly numbers of blocks with malaria cases in West Bengal from 2011 to 2021 are summarized in Fig. 1. There is a striking variation in both of the cases. The monthly number of malaria cases peaked in August 2012 (2155 cases), with other peaks recorded in July 2017 (2122 cases) and August 2017 (1984 cases) respectively. Peaks with malaria incident cases generally coincided with high monthly numbers of blocks with malaria cases. The data clearly indicate that malaria fever the malaria fever is quite prevalent through-out the year.

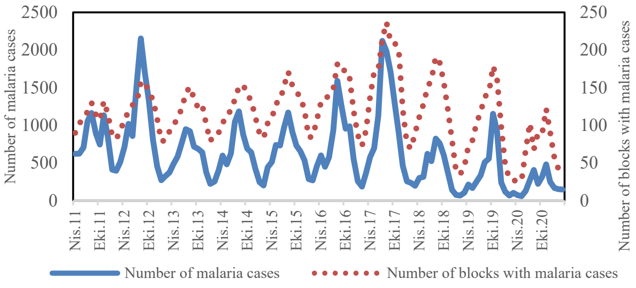

Fig. 1 Numbers of malaria cases and blocks with malaria cases from 2011 to 2021 in West Bengal

Table I represents summary statistics of number of malaria cases and monthly numbers of blocks with malaria cases during three different periods. The result shows that monthly average malaria cases are 768.25, 789.92 and 330.15 during 2012-14, 2015-17 and 2018-20 respectively.

TABLE I
DESCRIPTIVE STATISTICS

Period	Min	Max	Mean	SD
Monthly number of malaria cases				
2012-14	222	2155	768.25	394.971
2015-17	185	2122	789.92	490.169
2018-20	59	1152	330.15	255.585
Monthly number of blocks with malaria cases				
2012-14	79	158	116.7	22.781
2015-17	73	237	141.11	42.434
2018-20	26	191	94.43	47.791

Two sets of Boxplot (Figs. 2 and 3) with number of malaria cases and monthly numbers of blocks with malaria cases indicate a strongly seasonal pattern (with peak during rainy/ monsoon). Boxplot displays the value of 25th, 50th and 75th percentile. The whiskers extend to the most extreme data point during rainy/monsoon and autumn/post monsoon. However, compared to the years prior to 2015–17, yearly reported malaria cases during 2018–20 are on average lower. The maximum number of blocks over the three-time span are most strongly influenced by the rainy and autumnal seasons, as shown in Fig. 3. The boxplot displays the values of the 25th, 50th and 75th percentiles.

Based on the malaria cases, the incidence rate (1/100000) is constructed in three different periods, where all blocks (n = 341) are grouped into four categories: low incidence areas (0.00); medium incidence areas (0.01-50.00); high incidence areas (50.01-100.00) and very high incidence areas (> 100.01). Fig. 4 displays chorochromatic maps with raw malaria incidence rate in three different periods. During 2012-14 and 2015-17 periods high and very high incidence areas are located in western and central parts of West Bengal. 2015-17 records maximum concentration of high and very high incidence areas over the western, central and northern part of the state. On the other hand, 2018-20 records comparatively few high and very high incidence areas in the northern and central parts in earlier periods.

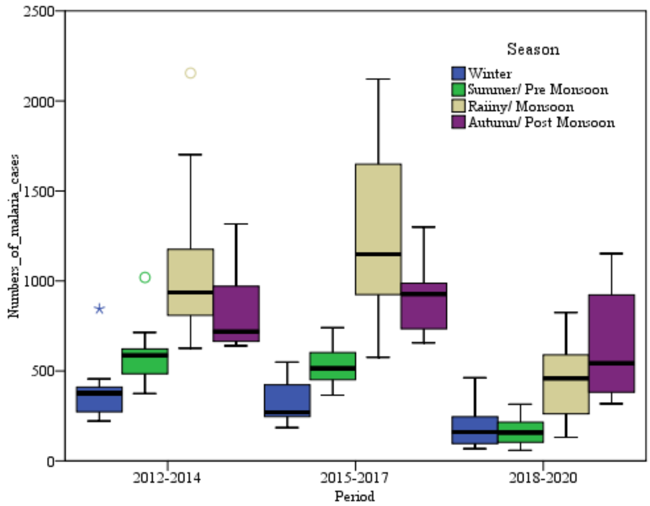

Fig. 2 Boxplots of seasonal distribution of numbers of malaria cases in three different periods, West Bengal

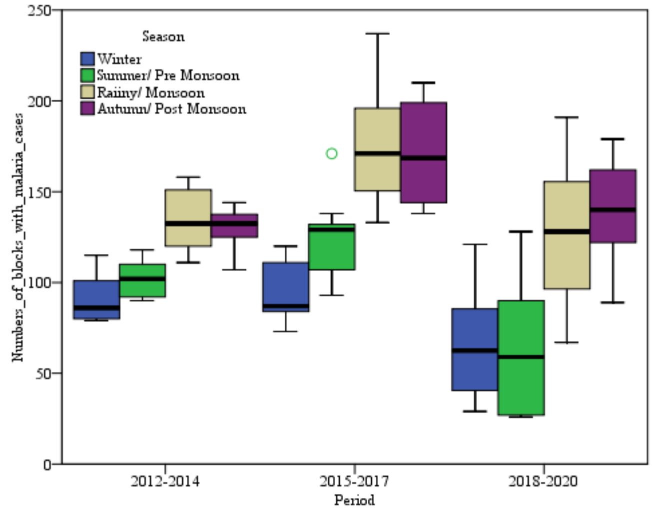

Fig. 3 Boxplots of seasonal distribution of numbers of blocks with malaria cases in three different periods, West Bengal

B. Spatial Autocorrelation of Malaria Fever

There is a significant positive spatial autocorrelation of malaria incidence for all three periods where Moran *I* statistics varies from 0.200 to 0.489. In the three periods during 2015-17 Moran-*I* statistics (Table II) sets highest value with 0.489 (p = 0.001) whereas minimum value is seen during 2018-20 period with 0.200 (p = 0.001). Fig. 5 displays Moran scatter plot of malaria incidence over three different periods which provides a classification of spatial association into four categories in the form of four quadrants.

TABLE II
SPATIAL AUTOCORRELATION ANALYSIS OF MALARIA INCIDENCE

Period	Moran's *I*	*E[I]*	z-value	P
2012-14	0.336	-0.0029	16.848	0.001
2015-17	0.489	-0.0029	21.4142	0.001
2018-20	0.200	-0.0029	8.3692	0.001

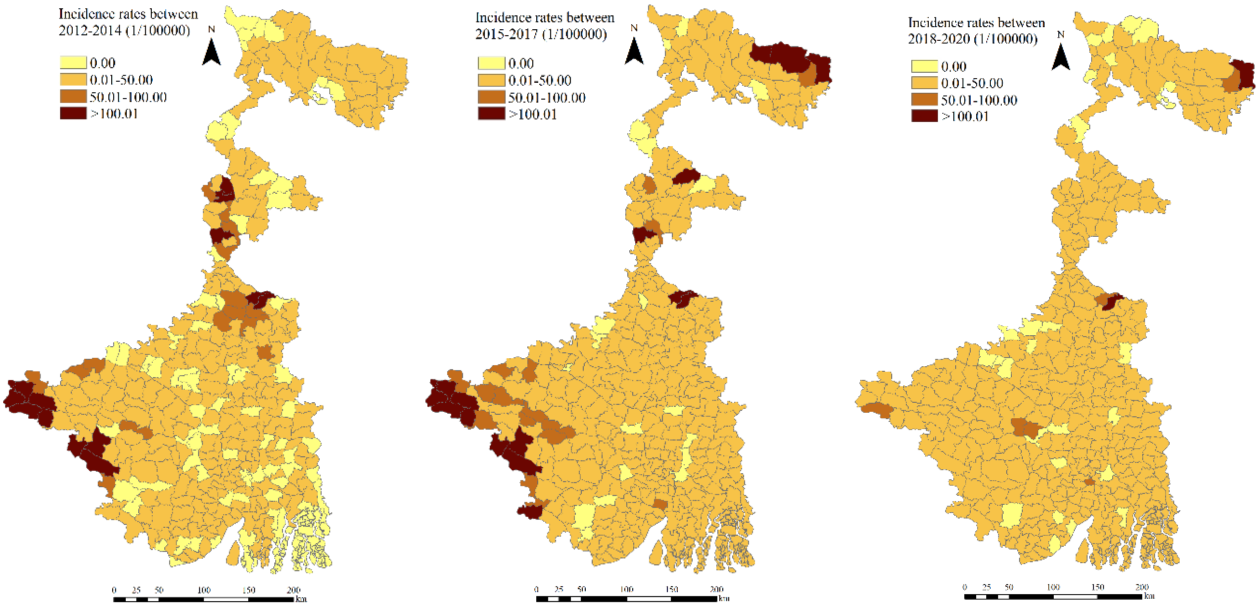

Fig. 4 Choropleth map showing raw malaria incidence rates in three different periods, West Bengal

C. LISA Analysis

LISA cluster map highlights four types of spatial autocorrelation of malaria fever incidence during three different periods. Areas with bright red (high-high clusters) and bright blue (low-low clusters) represent positive spatial autocorrelation while light red (high-low outliers) and light blue (low-high outliers) represent negative spatial autocorrelation. For all the cases high-high clusters are primarily concentrated in the western, central and northern parts and low-low clusters are found in the lower Gangetic plain (central-south) mainly and norther part of West Bengal during the stipulated time period (Fig. 6).

D. Local Geary Cluster Map

Univariate Local Geary classification generates four types of clusters: high-high (positive) and low-low (negative) spatial autocorrelation with other positive and negative where bright red represents high-high and light red as low-low cluster cores (Fig. 7). Over the three periods, high-high cluster cores mainly prevalent in the western and central part of the state of West Bengal. Low-low cluster cores are mainly concentrated in the northern and lower Gangetic plain during three periods The numbers are given within brackets in Figs. 6 and 7 indicates number of blocks in different clusters.

V. Discussion

To understand geographical or spatial epidemiology [12], [16], [17] of malaria fever, analysis of epidemiological data, prediction of outbreak, and hot spot analysis are critical part which is similar to the other studies [2], [18]-[21]. This study primarily focuses on the seasonal and spatio-temporal distribution of malaria fever incidence during the time periods of 2012-2020. From the analysis, seasonal variation is clearly visible over the time periods where maximum cases reported during monsoon/rainy and post-monsoon seasons [22]. As because mosquito borne malaria is positively related with rainfall and temperature, that is elaborated in different research work.

Apart from seasonal distribution, spatial mapping is an important tool to identify hotspots of malaria zone. The spatial autocorrelation and LISA analysis along with Geary are valuable tools to study how spatial patterns change over time. The spatial distribution pattern of malaria fever incidents is significantly clustered. From LISA analysis, it is shown that hotspots are mainly concentrated in the western part of the state.

This analysis shows that the incidence of malaria fever in West Bengal has high to low spatial autocorrelation during three periods. Progressively high-high clusters predominated during the study period in five blocks of the Purulia district in Western West Bengal, including Arsha, Jhalda-I, Jhalda-II, Bagmundi, and Balarampur. Coincidentally Western part of West Bengal shares interstate borders with Jharkhand and Orissa which ranked 4th and 5th states with maximum malaria cases in India according to 2018 report [18]. In a nutshell, neighboring blocks or districts share similar ecology, geography and social status etc. which help to give rise to a positive and negative association in the occurrence of Mosquito-borne diseases [23]. In this context Tobler's law or the First law of Geography is more applicable to the analysis of spatial autocorrelation [24]. Because location factor plays a vital role in disease distribution.

The results from different methods of this study indicate significant variation in the spatial distribution of malaria incidence in West Bengal and high incidence clusters are primarily persistently concentrated over the western part during 2012-2020 along with a strong seasonal pattern with a peak in rainy and autumn. The incidence of death caused by Malaria is comparatively less than other communicable diseases in India. Even in West Bengal, Dengue has been more serious issue for its wide spread nature from urban areas to rural parts. But malaria is a dominant disease in rural West Bengal from north to south. As per the published data by the Department of Health in West Bengal, principal malaria susceptible areas are Purulia, Bankura, and Paschim Midnapore in the southern and western parts of West Bengal and New Jalpaiguri districts in northern part of West Bengal.

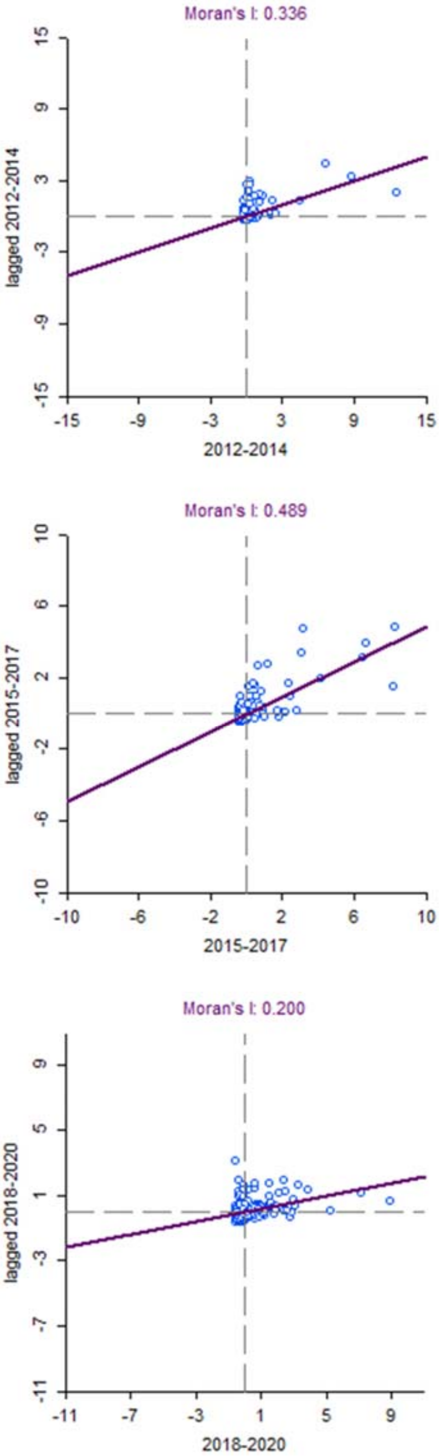

Fig. 5 Moran *I* scatter plot of malaria incidence in three different periods, West Bengal

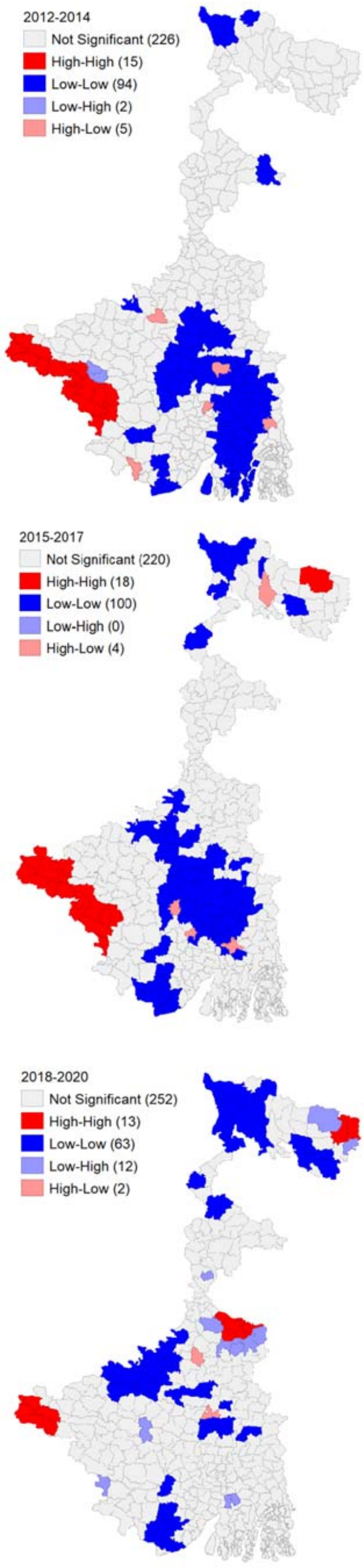

Fig. 6 LISA cluster map in three different periods, West Bengal

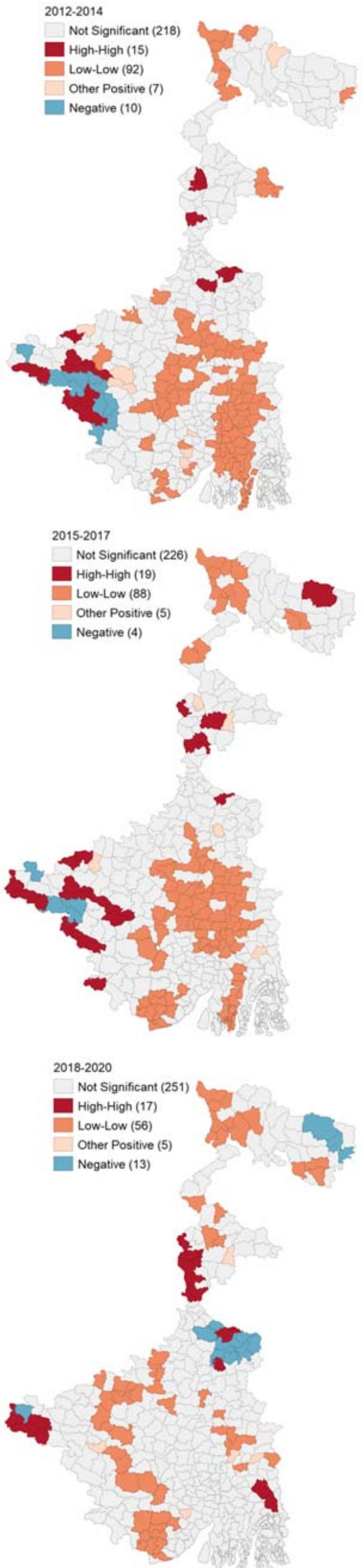

Fig. 7 Local Geary cluster map in three different periods, West Bengal

In reality, malaria has not disappeared from different parts of Bengal but it comes as a persistent disease again and a significant number of rural inhabitants have been affected by the ecologically and evolutionary modified antibiotic resistant different types of malaria carrying mosquito. But respective department of government is not worried about malaria and they are paying more attention to dengue as it is the cause of huge death tolls especially in the urban environments. They are addressing the issue properly due to malaria is less vulnerable in comparison to dengue. With an ignoring attitude from the policy making end, the incidence rate and related suffering have been increasing day by day. Living place and surrounding areas driven by local geographical factors are triggering the incidence of malaria in different parts of West Bengal. Changing living habitats across rural Bengal are becoming malaria-prone area.

There are certain limitations in this study. This work examines the geographic and temporal variation of malaria fever incidence and its clustering pattern including hot spot and cold spot regions in West Bengal using GIS tools but it does not focus on its underlying causes. Future research will examine the key socio-ecological factors like social, demographic, climatic and mosquito density affects the distribution and transmission patterns of malaria fever incidence [25]–[27].

VI. Conclusion

Applying different techniques in identifying the different degree of incidence zones of malaria across West Bengal, some specific pockets or malaria hotspots are marked and identified where the incidence rates are quite harmonious over different time periods. From this analysis, it is clear that malaria is not a disease that is distributed uniformly across the state; some specific pockets are more prone to be affected in particular seasons of each year. Disease ecology and spatial patterns must be the factors in explaining the real factors for higher incidence of this issue within those affected districts. Further study mainly by applying empirical approach is needed for discerning the strong relationship of this communicable disease and other associated affecting factors.

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