ORIGINAL ARTICLE

Application of Geospatial Technology for Infectious Disease Surveillance: A Study of Covid-19 Pandemic in North-east India

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Abstract

Background: The COVID-19 pandemic has shattered the global health system and caused havoc worldwide. Since there is no proper medication, non-pharmaceutical intervention methods are followed to mitigate viral transmission. For its proper implementation, it is crucial to track the spatial pattern of transmission and target those areas which require immediate action to control the spread of the pandemic. The geospatial technologies have established themselves as powerful tools that have substantial ability to track outbreak patterns in real-time, identify at-risk populations, and plan targeted intervention.

Methods: The study provides a robust methodological framework with three geospatial tools: Spatial Autocorrelation (Global Moran's I), Hot Spot Analysis (Getis-Ord Gi*), and Space-time scan statistic. The quantitative study was carried out exclusively for North-East India to track the COVID-19 outbreaks from April 2020 to December 2020.

Results: The results obtained indicate a gradual change of spatial distribution of the disease from cluster to random distribution at the global scale. But, eventually, the COVID-19 cases tend to form clusters again. Kamrup Metro, the district with the highest urban population, was reported constantly as a hotspot. Moreover, space-time clusters tend to expand in size over time.

Conclusion: The research study's findings provide an overview of the spatio-temporal pattern of COVID-19 in the study area and help the health officials and policy-makers in formulating effective management strategies and non-pharmaceutical intervention measures by targeting the high-risk areas. The study is a valuable guide towards implementing Geographic Information Science technologies in monitoring and tracking the pandemic.

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Keywords: COVID-19, Disease hotspot, Health information system, Pandemics

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Introduction

Our world is struggling to mitigate the unprecedented global health crisis with the rapid spread of the Coronavirus Disease 2019 (COVID-19) pandemic. The deadly contagion has created a significant knock-on effect on every aspect of human life. The emerging respiratory disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) reported its first case from Wuhan city, China, on 31st December 2019.[1] On 30th January 2020 World Health Organization (WHO) characterized COVID-19 as a Public Health Emergency of International Concern due to a sudden rise in coronavirus cases outside China.[1] Subsequently, on 11th March, deeply concerned by a sharp spike in cases, WHO declared COVID-19 a pandemic, pushing the risk beyond global health emergency.[1]

The highly transmittable zoonotic disease spreads from person to person via respiratory droplets from coughing or contaminated secretions on objects and surfaces.[2] Clinical manifestations of COVID-19 range from mild symptoms like fever, coughing, fatigue, headache, sore throat, and breathlessness[3] to severe complications such as pneumonia, respiratory failure, multi-organ failure, and septic shocks.[4] However, most of the deaths reported from COVID-19 are people having certain underlying medical conditions, including hypertension, cardiovascular disease, or respiratory disease, and older people are at high risk from COVID-19.[5] Globally, the total confirmed cases of COVID-19 have crossed 83 million with 1,812,995 deaths as of 31st December 2020.[6]

According to UNDP reports, as of mid-May, the daily COVID-19 fatalities exceeded deaths due to common causes such as malaria, suicide, road traffic accidents, and HIV/AIDS. It can become the main reason for death surpassing cancer and coronary disease in countries at the peak of the current wave.[7] Moreover, the COVID-19 pandemic and its containment measures will shrink the global economy by 5.2% this year, triggering the deepest recession since World War 2.[8] Nearly 50% of the worldwide workforce stands in immediate danger of losing their livelihood.[9] Additionally, the pandemic affects the psychological state of individuals and causes disruption, anxiety, stress, stigma, and xenophobia among them.[10] India stands at the second position after the USA with more than 10 million confirmed cases and reported 1,49,018 fatalities as of 31st December 2020.[11] The first COVID-19 case of India can be traced back to 30th January 2020 in Kerala.[12]

Currently, in the absence of a safe vaccine or therapeutics, non-pharmaceutical intervention (NPI) methods, including lockdown, quarantine, isolation, social distancing, restricting mass gathering, educational institution closure, protection of vulnerable groups, travel restrictions, hand and respiratory hygiene, and wearing a mask are effective measures to combat COVID-19.[7, 13] These prudent strategies are required to minimize the progression and severity of the outbreak. Since the vital characteristic of a pandemic is its spatial expansion, it is crucial to understand the spatial dynamics, transmission pattern, and nature of clustering of the disease and assist the health officials, policy-makers, and government in the effective implementation of NPI measures.[14]

The Geographic Information System (GIS) applications are considered a standard tool to track the transmission and evaluate the geographic pattern of the disease outbreak.[15] Geospatial tools have great potential to predict outbreaks, detect clusters, conduct surveillance, identify the vulnerable zones, and track the diffusion of infectious disease.[16-18] Numerous research studies investigated the application of GIS in mitigating different diseases as human rabies,[19] foot and mouth disease in animals,[20] malaria,[21] and Kala-azar.[22] Recently, after COVID-19, studies were carried out globally with the assistance of GIS technologies to explore specific aspects of the pandemic as the geospatial mechanism, prediction of COVID-19 trend, health and medical issues, planning and policies, public health competencies, social and economic consequences as well as the correlation between climatic factors and the infectious disease.[23-25] Moreover, studies utilizing GIS techniques such as Weighted Overlay Analysis and Analytical Hierarchy Process were conducted to identify vulnerable zones of COVID-19 in India[26] and Bangladesh.[18] At the global scenario, online Rasch Modelling was used to determine the countries at high risk from COVID-19. Authors reported that Iran, South Korea, Italy, Germany, Spain, China (Hubei), and France were top countries.[27] Thus, researchers conducted a series of studies utilizing geospatial technology to mitigate the global health emergency in different countries. But an in-depth comprehensive study on spatial dynamics of transmission, Spatio-temporal clustering, hotspot identification, and risk assessment of COVID-19 is scarce. The existing literature also lacks an exclusive methodology of spatial statistics that is capable of exploring the spatio-temporal clustering of COVID-19 at both global and local scales and evaluating the relative risk of each cluster. As far as North East India is concerned, it is seldom to find research works on COVID-19 using GIS, although literature highlighting socio-economic consequences of COVID-19 has been conducted. Thus, the principal aim of the research study is to explore the significant contribution of geospatial methods in formulating policies and plans to implement NPI methods and minimize the severity of COVID-19.

Therefore, the present study focuses on:

- Signifying the application of geospatial tools in health planning and management during the COVID-19 pandemic.
- Evaluating the nature of clustering of COVID-19 in North East India
- Identifying the hotspots of COVID-19 at the district level.
- Determining the space-time clusters of COVID-19 and estimating their magnitude of relative risk.

The research paper begins with an introduction describing the background of the research problem, outlining the objectives, and highlighting the significance of adopting a geospatial approach in scrutinizing the spatial dynamics of COVID-19 to mollify the severities of the pandemic. The following section provides a brief account of the study area, data, and methodology applied. Next, the results are discussed in the following sections. Lastly, the discussion and conclusion summarize the main findings and key takeaway from the research study.

Study Area

North-East India (North Eastern Region: NER) is the easternmost part of India comprising eight states: Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, and Tripura. The latitudinal extent of the region ranges from 22° N to 29° 5' N, and the longitudinal extent ranges from 88° E and 97° 30'E. The region covers an area of 262,179 km2 and comprises a population of 45,772,188 persons.[28] North East India reported its first case lately on 24th March 2020 in Manipur. As of 31st December 2020, North East India has reported more than 2 lakh cases (Figure 1).[29]

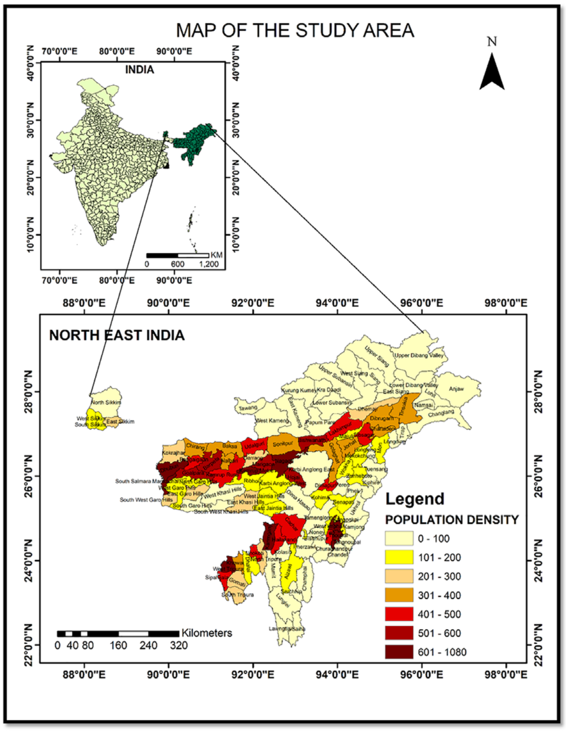

Figure 1: Location map of the study area

Methods

The author collected data regarding COVID-19 cases from an online dashboard "Districtwise Corona Tracker India" available at "https://howindialives.com/gram/coronadistricts/" from 24th March 2020 till 31st December 2020. Temporally, these data are updated daily and spatially; the daily confirmed cases of COVID-19 are aggregated at the district level.

Using the geographic location information from the COVID-19 dataset, we have allocated the case counts to the appropriate districts in a geographic information systems compatible file we obtained from the "DIVA-GIS" online platform available at "https://www.diva-gis.org/gdata". Moreover, to acquire the number of daily new cases, we subtracted the previous day's total cases from the current day's total cases since COVID-19 cases were reported in cumulative counts. The author used cumulative incidence rate of COVID-19 cases per 10,000 population for each month to perform both Spatial Autocorrelation (Global Moran's I) and Hot Spot Analysis (Getis-Ord Gi*). However, daily confirmed cases were used to run the Space-time scanning using a discrete Poisson approach. The research study applied three distinct cluster detection methods for a detailed analysis of spatiotemporal clusters of COVID-19 and the relative risk of each cluster in the study area.

Spatial Autocorrelation (Global Moran's I)

The Global Moran's I simultaneously estimate the spatial autocorrelation based on both feature values and feature locations to verify whether there is a significant formation of clusters at the global level. A statistically significant cluster with a positive z-score indicates that the spatial distribution of values is clustered, whereas a negative z-score indicates dispersed spatial distribution of values.

The Moran's I Index for spatial autocorrelation is calculated as[30]

$$I = \frac{n}{S_0}\,\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2}$$

Where, Z_i is the deviation of an attribute for feature i from its mean (x_i-$\bar{X}$) and $w_{i,j}$ is the spatial weight between feature i and j, n is the total number of features, and S_0 is the aggregate of all spatial weights.

Hot Spot Analysis (Getis-Ord Gi*)

This tool can identify statistically significant spatial clusters of high values (hot spots) and low values (cold spots) at a local spatial level. The tool evaluates the formation of clusters based on a z-score, P value, and confidence level bin (Gi_Bin) for each feature in the Input Feature Class. A positive z-score signifies a hot spot with high values, and a negative z-score signifies a cold spot with low values. Getis-Ord Gi* local statistics is calculated as[31]

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}\, x_j - \bar{X}\sum_{j=1}^{n} i,j}{S\sqrt{\dfrac{n\left[\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}$$

Where x_j is the attribute value for feature j and $w_{i,j}$ is the spatial weight between feature i and j, and n equals the total number of features.

Space-time Scanning Using a Discrete Poisson Approach

The Spatio-temporal clusters of COVID-19 were identified using the space-time scan statistic with the discrete Poisson method as the probability model in SaTScan v9.6.[32] The method applied a cylindrical scanning window where the base represents the spatial scanning window, and the height reflects the temporal scanning window. The significant clusters with elevated risk were identified by computing the maximum likelihood ratio, and the Monte Carlo replications (999 simulations) of the datasets were applied to determine the p-values. The null hypothesis stated: "COVID-19 possesses a constant risk with a particular intensity proportional to population at risk throughout the study area", whereas the alternative hypothesis stated: "the study area witnesses formation of space-time clusters of COVID-19 with different values of relative risk". In this research study, we have set the maximum cluster size as 20% of the population to avoid large clusters and set the temporal window to 90% to cover the maximum interval of time with the time precision of 1 day for reading cases of each date.

The maximum likelihood ratio was calculated as:

$$\frac{L(Z)}{L_0} = \frac{\left(\frac{n_Z}{\mu(Z)}\right)^{nz}\left(\frac{N-n_Z}{N-\mu_{(Z)}}\right)^{N-nz}}{\frac{N}{\mu(T)}^{N}}$$

Where $L(Z)$ is the likelihood cylinder for cylinder Z, L_0 is the likelihood function for the null hypothesis (H_0), n_Z is the number of cases in a cylinder, $\mu_{(Z)}$ is the number of expected cases in a cylinder Z, N is the total number of observed cases for entire study area across all the interval of time, $\mu(T)$ is the total number of expected cases for entire study area across all the interval of time.

The relative risk of a cluster can be estimated as:

$$RR = \frac{C/e}{(N-C)/(N-e)}$$

Where C is the total number of cases in a cluster, e is the total number of expected cases in a cluster, N is the total number of observed cases in the entire study region.

The first two spatial statistics were performed using ArcGIS 10.5, and space-time scan statistics using Poisson Discrete model were run in SaTScan v9.6. All the spatial statistics tools have evaluated specificsignificant results discussed in the following section.

Results

After implementing three distinct geospatial tools, the research study has come up with significant results highlighting the robustness and the reliability of the methods.

Spatial Autocorrelation (Global Moran's I)

The Moran's I index was calculated to evaluate the nature of spatial propagation of the disease. The results of the Moran's I Index are represented in Table 1. The results obtained from the spatial tool signifies that during the initial stage of the pandemic, COVID-19 cases were significantly clustered at the global level. But, the spatial distribution of the disease randomly occured due to the fast transmission of the pandemic throughout the study area. The initial months of April, May, June, and July witnessed significant clustering with p-values 0.067, 0.095, 0.049, and 0.015, respectively. But, later on, in August, September, and October, the spatial transmission of the contagion shifted towards random distribution with a z-score of 0.514, 0.371, and 0.899, respectively. However, significant clustering with p-values of 0.012 and 0.087 was observed during the previous two months of November and December.

Hot Spot Analysis (Getis-Ord Gi)*

The Hot Spot Analysis (Getis-Ord Gi*) is one of the standard tools applied in identifying hotspots or local clusters of any phenomenon on the earth's surface. In this study, the geospatial tool was used to identify hotspots of COVID-19 at the district level in the study area to understand the temporal and spatial evolution of the disease dynamics (Figure 2). At the outset of the pandemic, certain districts of Assam (Kokrajhar, Dhuburi, South Salmara Mankachar, Bongaigaon, Goalpara, Kamrup Metro, and Kamrup Rural) and Meghalaya (Ribhoi, West Jaintia Hills, East Khasi Hills, and West Khasi Hills) were identified as the hotspots of the disease in April, and imported cases

Table 1: Spatial Autocorrelation (Global Moran's I) of COVID-19 in North East India for April-December 2020.

Months	Moran's Index	Expected Index	z-score	p-value	Distribution	Confidence Level
April	0.082	-0.009	1.827	0.067	Clustered	90%
May	0.072	-0.009	1.664	0.095	Clustered	90%
June	0.084	-0.009	1.967	0.049	Clustered	95%
July	0.027	-0.009	2.417	0.015	Clustered	95%
August	0.010	-0.009	0.514	0.606	Random	N.A
September	0.005	-0.009	0.371	0.710	Random	N.A
October	0.038	-0.009	0.899	0.368	Random	N.A
November	0.129	-0.009	2.513	0.012	Clustered	95%
December	0.084	-0.009	1.709	0.087	Clustered	90%

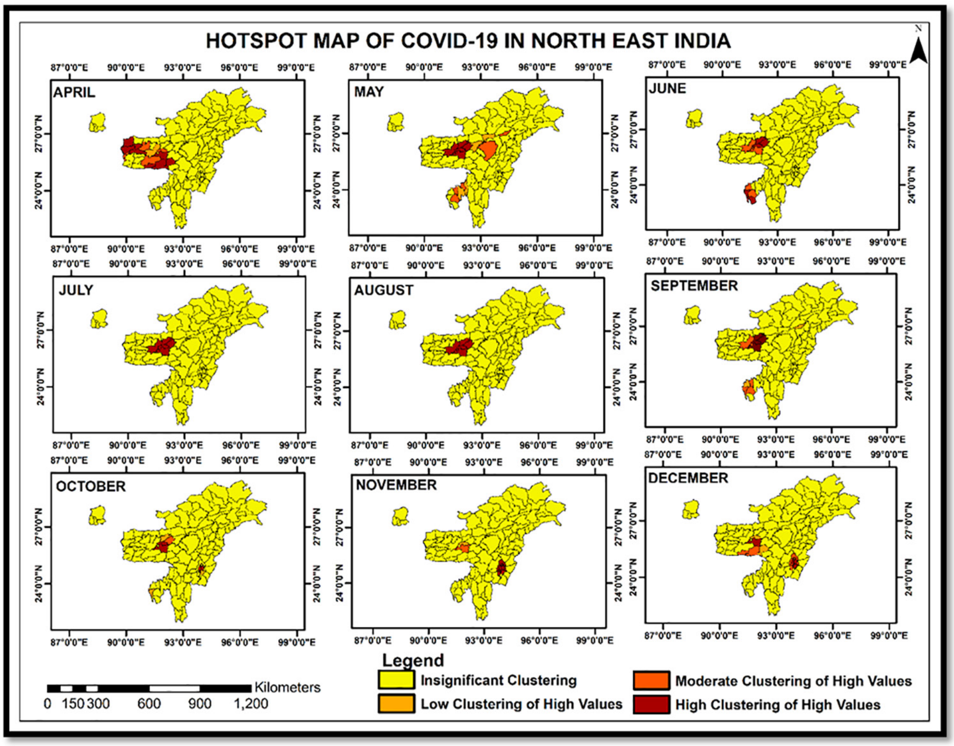

Figure 2: Hotspot Map of COVID-19 in North East India for April-December, 2020.

transmitted the infection in these areas from outside. Subsequently, in May, new clusters were identified towards middle Assam (Karbi Anglong East, Nagaon, and Biswanath), and the clusters observed in the western Assam during April disappeared. Moreover, the new cluster emerged in the state of Tripura, including Dhalai, Khowai, Gomati, North Tripura, and Unokoti. In June, the clusters of middle Assam were no longer observed since cases started rising in number equally everywhere. But few districts of Tripura were still in a vulnerable state.

July and August observed a rapid spike in the number of cases throughout the study area. In September, the districts of Tripura, including Shipajhila, Gomati, Khowai, and West Tripura re-emerged as hotspots. However, during October, November, and December, few districts witnessed a rapid increase in COVID-19 cases. Surprisingly, only one district of Assam, Kamrup Metro, was identified as a hotspot in November and December. Moreover, in December few districts of Meghalaya (Ribhoi, South West Khasi Hills, East Khasi Hills, and West Jaintia Hills) were also observed as hotspots.

Thus, the cluster, including Kamrup Rural, Kamrup Metro, Morigaon, Darrang, and Ribhoi was constantly identified as a hotspot from April until September. Relaxing the lockdown, withdrawing certain restrictions of people's movement, lack of awareness, reluctance to follow the rules and regulations, and rapid human mobility have increased the virus's spread in these areas. However, this cluster has weakened overtime in October, New clusters appeared in Manipur during November and December.

Space-time Scanning Using a Discrete Poisson Approach

The space-time scanning window with a discrete Poisson approach was run to follow the emerging space-time clusters of COVID-19 (Figure 3). Two significant clusters were observed in East Khasi Hill district and Bongaigaon in April. The month of May witnessed seven significant clusters at different time intervals. The four out of seven clusters comprise more than one district. In June, we observed eight significant emerging clusters with elevated risk, increasing to twelve in July. The five clusters were distinctly large, comprising more than one district. In both August and September, we observed ten significant clusters. In August four clusters and in September five clusters comprised more than one district. In October, November, and December, the clusters reported weres nine, si,x, and seven, respectively. Therefore, a gradual expansion in the space-time clusters is observed in the later months, indicating the disease's rapid transmission to the areas that were earlier not affected by the disease in the initial stage (Table 2).

Discussion

Spatial transmission is one of the most striking characteristics of epidemics, mainly determined by epidemic mechanism, human mobility, and control strategy.[33] Geospatial statistics has widespread use in

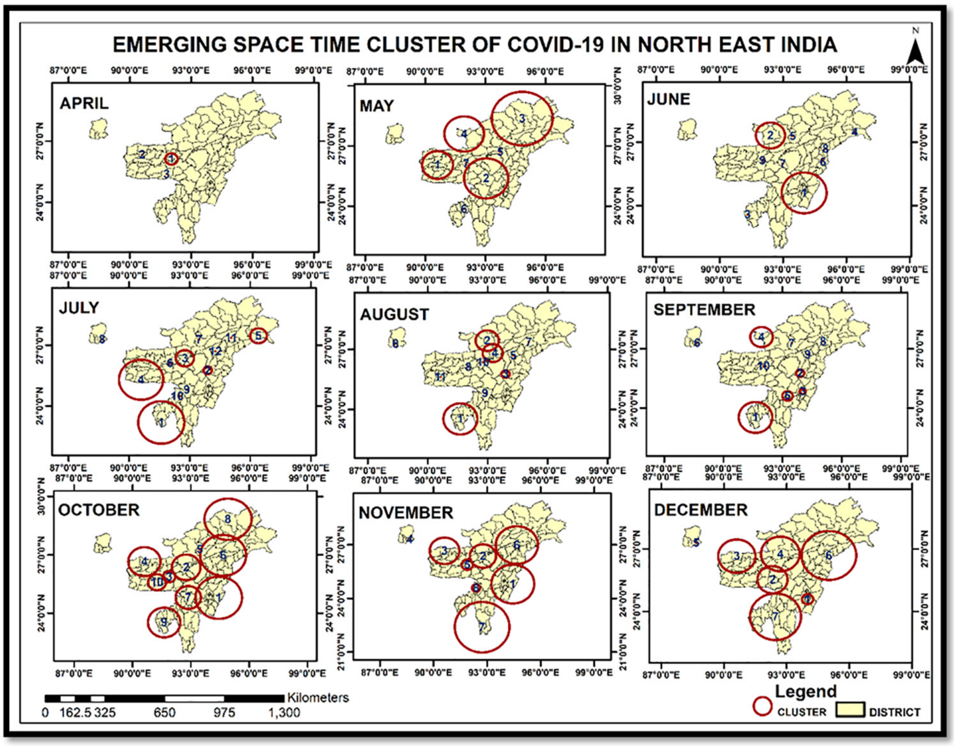

Figure 3: Space-Time clusters of COVID-19 in North East India for April-December, 2020.

Table 2: Space-time scan statistics (discrete Poisson approach) of COVID-19 in North East India for April-December, 2020.

Month	Cluster	Start Date	End Date	No. of Location	P value	RR
April	1	01/04/2020	30/04/2020	2	0.332	5.03
	2	28/04/2020	30/04/2020	1	0.001	91.23
	3	14/04/2020	30/04/2020	1	0.001	40.36
May	1	30/05/2020	31/05/2020	10	0.001	5.84
	2	23/05/2020	31/05/2020	17	0.001	2.77
	3	30/05/2020	31/05/2020	16	0.001	5.45
	4	30/05/2020	31/05/2020	3	0.001	8.38
	5	25/05/2020	31/05/2020	1	0.001	24.00
	6	06/05/2020	31/05/2020	1	0.001	16.57
	7	22/05/2020	31/05/2020	1	0.001	26.27
June	1	08/06/2020	30/06/2020	17	0.001	3.66
	2	30/06/2020	30/06/2020	4	0.453	2.40
	3	04/06/2020	30/06/2020	1	0.001	7.94
	4	06/06/2020	30/06/2020	1	0.001	8.26
	5	14/06/2020	30/06/2020	1	0.001	4.77
	6	30/06/2020	30/06/2020	1	0.001	20.20
	7	05/06/2020	30/06/2020	1	0.001	1.87
	8	11/06/2020	30/06/2020	1	0.002	2.39
	9	20/06/2020	30/06/2020	1	0.001	16.06
July	1	18/07/2020	31/07/2020	8	0.001	2.95
	2	22/07/2020	31/07/2020	2	0.001	4.81
	3	31/07/2020	31/07/2020	2	0.001	3.93
	4	28/07/2020	31/07/2020	10	0.001	2.11
	5	28/07/2020	31/07/2020	2	0.001	6.60
	6	05/07/2020	31/07/2020	1	0.001	34.14
	7	10/07/2020	31/07/2020	1	0.001	10.35
	8	14/07/2020	31/07/2020	1	0.001	4.41
	9	31/07/2020	31/07/2020	1	0.001	4.37
	10	13/07/2020	31/07/2020	1	0.001	2.03
	11	31/07/2020	31/07/2020	1	0.001	4.78
	12	31/07/2020	31/07/2020	1	0.001	5.20

August	1	18/08/2020	31/08/2020	8	0.001	3.01
	2	07/08/2020	31/08/2020	3	0.001	3.91
	3	05/08/2020	31/08/2020	2	0.001	2.72
	4	31/08/2020	31/08/2020	2	0.001	4.68
	5	24/08/2020	31/08/2020	1	0.001	4.61
	6	30/08/2020	31/08/2020	1	0.001	34.39
	7	05/08/2020	31/08/2020	1	0.001	3.59
	8	05/08/2020	31/08/2020	1	0.001	15.33
	9	13/08/2020	31/08/2020	1	0.001	2.76
	10	30/08/2020	31/08/2020	1	0.001	1.42
	11	27/08/2020	31/08/2020	1	0.990	1.44
September	1	04/09/2020	30/09/2020	8	0.001	3.70
	2	09/09/2020	30/09/2020	2	0.001	3.27
	3	05/09/2020	30/09/2020	2	0.001	2.09
	4	14/09/2020	30/09/2020	2	0.001	2.41
	5	28/09/2020	30/09/2020	2	0.001	6.14
	6	04/09/2020	30/09/2020	1	0.001	3.69
	7	04/09/2020	30/09/2020	1	0.001	15.70
	8	04/09/2020	30/09/2020	1	0.001	1.89
	9	07/09/2020	30/09/2020	1	0.001	3.78
	10	04/09/2020	30/09/2020	1	0.001	12.28
October	1	07/10/2020	31/10/2020	18	0.001	5.20
	2	05/10/2020	31/10/2020	8	0.001	0.01
	3	07/10/2020	31/10/2020	2	0.001	7.50
	4	05/10/2020	31/10/2020	8	0.001	0.01
	5	09/10/2020	31/10/2020	1	0.001	23.09
	6	07/10/2020	31/10/2020	18	0.001	0.15
	7	05/10/2020	31/10/2020	7	0.001	0.04
	8	08/10/2020	31/10/2020	7	0.001	6.65
	9	06/10/2020	31/10/2020	7	0.001	2.22
	10	05/10/2020	31/10/2020	3	0.001	0.08
November	1	06/11/2020	30/112020	19	0.001	7.51
	2	04/11/2020	30/11/2020	8	0.001	0.01
	3	04/11/2020	30/112020	8	0.001	0.07
	4	07/11/2020	30/11/2020	1	0.001	12.33
	5	06/11/2020	30/112020	2	0.001	4.60
	6	04/11/2020	30/11/2020	18	0.001	0.26
	7	05/11/2020	30/112020	8	0.001	3.55
	8	04/11/2020	30/11/2020	2	0.001	0.02
December	1	05/12/2020	31/12/2020	5	0.001	8.92
	2	05/12/2020	31/12/2020	6	0.001	4.94
	3	05/12/2020	31/12/2020	9	0.001	0.02
	4	05/12/2020	31/12/2020	9	0.001	0.04
	5	05/12/2020	31/12/2020	1	0.001	15.93
	6	05/12/2020	31/12/2020	19	0.001	0.04
	7	05/12/2020	31/12/2020	18	0.001	0.05

epidemiological research: to generate detailed maps to understand the spatial pattern of the disease, it's the correlation with potential risk factors, to identify hotspots and vulnerable regions. Medical Geography has become extremely useful in addressing the spatial issues of epidemics through concepts, methods, and quantitative techniques. Thus, the current research intends to comprehend the disease outbreak through a geospatial approach since GIS is a potential resource for risk analysis and to forecast the spatial propagation of an epidemic. According to the research findings, similar to previous literatures,[34, 35] the initial phase of the outbreak witnessed significant clustering of COVID-19 cases. After the initial outbreak, the COVID-19 cases continued to spread to most districts, and cases were growing dramatically. Therefore, a random distribution of cases was reported in August, September, and October. However, the disease outbreak was controlled after a while by implementing effective NPI methods, and few clusters reported where the number of cases was increasing. Thus, the last two months again witnessed clustering of COVID-19 cases at the global scale. Therefore, NPI methods, namely mandatory face mask in public, isolation or quarantine, social distancing, and traffic restriction, have effectively controlled the spread of COVID-19,[36] especially during the pandemic when there was no efficient vaccine or treatment for this novel infectious disease.

Moreover, the districts with high population density such as Kamrup Rural, Kamrup Metro, Morigaon, and Darrang were continuously reported as a hotspot for most of the time. Additionally, Kamrup Metro, with the highest urban population (82.9%)[28] was the most affected district, and it was constantly reported as a hotspot from April to December. Thus, these findings y signify that districts with dense populations and urban areas were more vulnerable to the disease outbreak.[37] Another surveillance tool to determine the active and emerging Spatio-temporal clusters of COVID-19 is prospective space-time scan statistics.[32] Desjandis et al.[38] and Gomes et al.[39] have utilized this tool for rapid surveillance of COVID-19 cases in the USA and Brazil, suggesting that health officials widely use scan statistics to evaluate the potential risk of active space-time clusters and prevent future outbreaks. In the current study, the results obtained from the space-time scan statistics show that both the number of clusters and their size increased over time, highlighting the characteristic of high transmission efficiency of the disease outbreak.[40] Most importantly , the advantage of space-time scan statistics over hotspot analysis is apart from identifying the emerging areas of concern and tracking the previously detected clusters' characteristics, the statistical tool also determines the relative risk of each cluster.[32] Thus, the identification of clusters and their relative risk will help prioritize areas while allocating resources, developing evidence-based policies, strengthening public health preparedness, and enabling the government to take decisions regarding NPI measures with greater precision. Therefore, the research study was an effort to follow a geographical approach in monitoring the COVID-19 pandemic.

Conclusion

In recent times, the emergence of the COVID-19 pandemic has heightened the applicability of GIS to understand the outbreak through a geospatial approach. The current research formulated a hybrid methodological framework of geospatial tools to understand the spatiotemporal dynamics of the disease outbreak for proper planning, decision-making, and resource allocation. Moreover, the research highlights the potential ability of geospatial technologies to understand the transmission dynamics and mechanism of infectious disease and formulate proper plans during a disease outbreak. Thus, the study contributed to the emerging discipline of health geography.

The significant result obtained from the geospatial methods signifies the robustness and reliability of GIS technologies in mollifying the severity of the pandemic. The study depicts the spatial dynamics of the pandemic from cluster to random distribution over time in the study area and ultimately reported clustered distribution during the last two months. Moreover, the study identifies certain districts constantly as hotspots and suggests government and health officials take immediate steps in monitoring the disease outbreak in those areas. A strong tendency to expand over time was seen among the emerging and active space-time clusters detected in the study area. The geospatial tools and the space-time scan statistics applied in the study can be rerun with the updated data for timely surveillance and monitoring of COVID-19 in the study area.

Thus, efficient use of geospatial data and mapping technologies can support the government, health officials, and policy-makers to prioritize areas while allocating resources and implementing various quarantine and isolation measures to control viral transmission. GIS technologies play a vital role in mitigating disease outbreaks. This study highlights the importance of a few powerful GIS tools among numerous methods that can be implemented in a limited time frame to effectively inform public health officials and decision-makers about the spatial and temporal dynamics of the disease outbreak. The methodological framework carried out in the research study can be used extensively for visualization and exploratory spatial analysis to gain insights into any disease outbreak.

Conflicts of interest: None declared.

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