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Geospatial Clustering and Hot Spot Detection of COVID-19 Incidence in 2020: A Global Analysis

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Abstract

Emergence and spread of Covid-19 initiated diversified researches based on spatial analysis in visualization, exploration, and modelling of this infection. This short communication is an attempt to comprehend the geographic distribution and spatial clustering of Covid-19 in year 2020. Main objective is to spatially analyze Covid-19 incidence rates, identification of hotspots and clusters outliers at global level. Monthly data of reported cases were taken from World Health Organization dashboard and situation reports. Incidence rate was calculated for each country for each month. Spatial autocorrelation techniques of Global Moran are I and Anselian Local Moran's I were used to examine the spatial clustering and outlier's detection of Covid-19 incidence in all months of the year. Hotspots and Coldspots variations are examined by using Getis-Ord G*. Mapping was executed in ArcGIS Pro environment. Results reveal significant spatial variation of Covid-19 incidence in WHO regions in different months of pandemic year 2020. Hotspots and high clustering of the disease incidence shows a shift from Western pacific towards Europe and Americas from January to April. Eastern Mediterranean countries also became a part of disease hotspots from the month of July leaving Africa as coldspot during whole year. Highest Moran's I value of 0.32 with highest z-score of 14 reflects the highly clustered pattern of this pandemic incidence in the month of December in contrary to least clustering of the disease with lowest Moran's I of 0.02 and z-score of 1.8 in June. Statistically significant variations in disease clustering pattern provides an opportunity for epidemiologists to further explore the disease incidence from ecological perspective.

Keywords

Covid-19, Incidence rate, Hotspot analysis, Cluster outlier analysis, Global Spatial Autocorrelation

1 INTRODUCTION

Coronavirus disease (COVID-19) is recognized as the global biological disaster. This disease was reported for the first time in Wuhan, China. During its early outbreak intensive population movement converted the outbreak into epidemic. By the time, this infectious disease spread so fast not only to other parts of China but also to various countries of Asia, Europe, North and South America, Australia and Africa as well. Hence, on 11th March, 2020 the WHO declared COVID-19 as pandemic and global health emergency (ERS 2020). By the end of year 2020, over 80 million cases and over 1.7 million deaths globally occurred since the start of this pandemic (WHO 2021).

The COVID-19 is full of unknown facts, and many of them have a spatial dimension that lead to understanding the phenomenon as geographical and potentially map-able (Franch-Pardo et al. 2020). COVID-19 offers a wide range of opportunity for the researchers worldwide but "spatial spread" of the disease is major dimension from the perspective of medical geography and epidemiology. Several studies use spatial analysis through Geographical Information System (GIS) in ecological exploration of COVID-19 pandemic (Li et al. 2020; Rex et al. 2020). Application of spatial statistical techniques helps to understand the spatial heterogeneity in diseases transmission and identification of significant risk regions especially COVID-19. A number of applications of spatial statistical models are used to comprehend the trend and transmission of COVID-19 (Gayawan et al. 2020; Gomes et al. 2020; Fatima et al. 2021). Hohl et al. (2020) advocate geospatial methods of spatial autocorrelation, space time scan statistics, hot spot and clustering analysis in GIS environment as an effective surveillance tool in spatial epidemiology and provide a profound way to analyze the complex geographic pattern of disease incidence and transmission. Significant knowledge of spatial clusters provides a baseline approach for health researchers to understand the spatial pattern of disease occurrence and beneficial for policy formulation to manage spatial spread of disease incidence (Murad et al. 2020). Therefore, current research is from the domain of geographical epidemiology, which can be define as the detection of spatial and temporal patterns of disease with target of formulation of hypothesis about etiological factors of that disease (Rezaeian et al. 2007). This study aims to provide the geospatial analysis of COVID-19 pandemic for a year 2020. To attain this objective, we examine the spatial distribution of COVID-19 crude rate on global scale through the application of global and local spatial autocorrelation techniques of Cluster detection and Hotspot analysis. Many studies use cluster and hotspot analysis for exploring this disease at regional, country and city level (Cavalcante et al. 2020; Lakhani 2020; Mollalo et al. 2020; Yang et al. 2020). Shariati et al. (2020) did spatial temporal analysis of COVID-19 at global level for two months (March-April); however this study will provide a global analysis of geographical distribution and spatial clustering of COVID-19 crude rate using spatial statistical methods in GIS.

2 MATERIAL AND METHODS

To meet the objectives of this study, COVID-19 data was collected from WHO situation reports. The cumulative number of COVID-19 reported cases were collected at the end of each month for every country and political territories. To calculate the crude rate, the population estimates for each country and territory were taken from the Worldometer for mid-July 2020 (Worldometer 2020). Geodatabase of the study is created and managed in 'world political boundaries' feature class at projected coordinate system of WGS 1984 Web Mercator Auxiliary Sphere in ArcGIS Pro 2.6 for executing spatial analysis of COVID-19 crude rate.

For purposeful explanation we adopt grouping of countries into WHO regions; African Region, Region of the Americas, South-East Asia Region, European Region, Eastern Mediterranean Region, and Western Pacific Region (WHO 2021).

2.1 Getis-Ord G^* (Hot Spot Analysis)

Hot spot analysis was carried out by using Getis-Ord G^* (Ord et al. 2001). It works by computing Getis-Ord G^* statistics for every COVID-19 crude rate. Resultant z-score and p-value for every feature explains where cluster of high values (hot spots) and low values (cold spots) exists. High positive z-score determine the more intense clustering of high values while high negative z-score values determine the intense clustering of low values. Computation is done within the context of neighboring feature value. To be a statistically significant hot spot, a feature will have a high value and be surrounded by other features with high values as well. The local sum for a feature and its neighbors is compared proportionally to the sum of all features. To apply Getis-Ord G^* in current research optimized hot spot analysis is run first to examine a threshold distance for better results. Later, hot spot analysis for every month was performed at fixed distance band ranging from 3414km to 4014km to gain significant hot and cold spots.

2.2 Anselin local Moran's *I* (Spatial Cluster Outlier)

Spatial autocorrelation is a technique applied to examine the spatial pattern of COVID-19 incidence using Global Moran's *I* (Moran 1950) and Anselin Local Moran's *I* (Anselin 1995). Anselin Local Moran's *I* is used in comparable to Global Moran's *I* for visualization of clusters and outliers (Bivand et al. 2009).We applied this technique to identify statistically significant clusters and outliers in global distribution of COVID-19. Output of analysis is visualized in four major groups: Two for clusters and two for outliers. High-High (HH) and Low-Low (LL) clusters identify similar country features with high or low COVID-19 incidence respectively. High-Low (HL) and Low-High (LH) identifies outliers with high COVID-19 incidence surrounded by countries of low COVID-19 incidence and vice versa.

2.3 Global Moran's *I* (Global Autocorrelation)

Spatial autocorrelation is the significant tool of spatial statistics in GIS environment to measure the correlation between nearby objects (Gangodagamage et al. 2008). Positive autocorrelation is reported when events closer to each other have similar values. Two important statistics to measure the spatial autocorrelation are Global Moran's *I* and Geary's *I*. Global Moran's index is the most popular method applied currently for computing Global spatial autocorrelation of COVID-19 incidence between neighboring countries at a fixed distance band width of 4614 km (Li et al. 2020; Shariati et al. 2020). The value of Moran's index varies from –1 to +1. Positive Global Moran's I value indicates a strong positive correlation in neighboring countries proving significant clustered pattern of COVID-19 incidence. Negative Moran's *I* represent negative correlation between neighboring feature while value closer to or equal 0 indicates no clustering in distribution pattern (Cao et al. 2020; Hazbavi et al. 2020; Li et al. 2020).

3 RESULTS

3.1 COVID-19 Crude Rate Distribution

Global distribution of COVID-19 crude rate in Figure 1a and 1b shows the propagation of disease across countries. In late December, 2019 China was the only country with this epidemic but in January, 2020 COVID-19 propagate to 19 more countries, nine from Western Pacific, four from Southeast Asia, USA and Canada from Americas, three from Europe and one from Eastern Mediterranean (WHO 2020) with highest crude rate in China (0.5 cases per 100K). February, brings 36 more counties into list with South Korea showing the highest COVID-19 crude rate (6 cases/100k), rest of the effected countries experienced <3 cases/100k. By the end of March, 2020 COVID-19 has spread to 146 countries globally with United States as leading country of COVID-19 cases spreading over its 50 states and New York as main epicenter (Mollalo et al. 2020). Hence, by the end of March, this disease affected almost 0.75 million people and thousands of death. Several European countries including Italy, Spain, Switzerland, Germany, France, Belgium, and United Kingdom experienced high COVID-19 crude rate.

Through 30th April, WHO reported highest number of COVID-19 cases in Europe (1.4 million) and Americas (1.2 million) with a high crude rate of >100 cases/100K. But South and Central Africa experienced lowest incidence of <4 cases/100K. By 30th May, COVID-19 propagated towards Eastern Mediterranean region. Fifty-five countries of the world experienced high incidence rate of >150 cases/100K in this month. Situation by 30th June, shows a random distribution with a low incidence in central Africa and Western Pacific and high incidence in Europe, Americas, and Eastern Mediterranean regions.

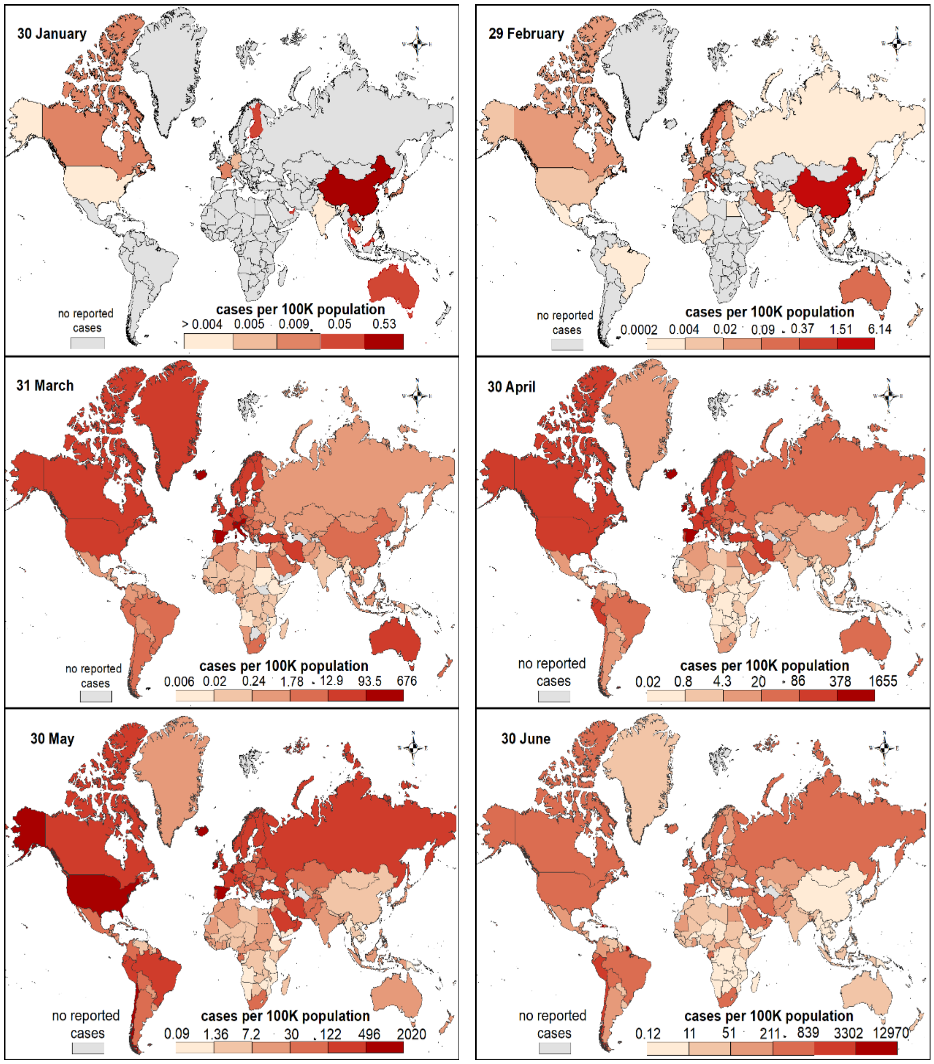

Figure 1a. Global COVID-19 crude rate per 100K population (January–June 2020).

By 30th July, United States COVID-19 cases reached to 4.3 million cases, followed by 2.5 million cases in Brazil, 1.6 million in India and 0.8 million in Russia. However, the highest rate of (465 to 6000 cases/100K) was recorded for 43 countries from Americas, Europe, and Eastern Mediterranean regions. August, and September, showed similar trend of COVID-19 crude rate as shown in Figure 1b. High-rate countries in these months includes from South Americas, Eastern Mediterranean, and a few from Europe regions. Analysis also reveals that COVID-19 incidence in USA decreased from the month of August, in comparison with previous months.

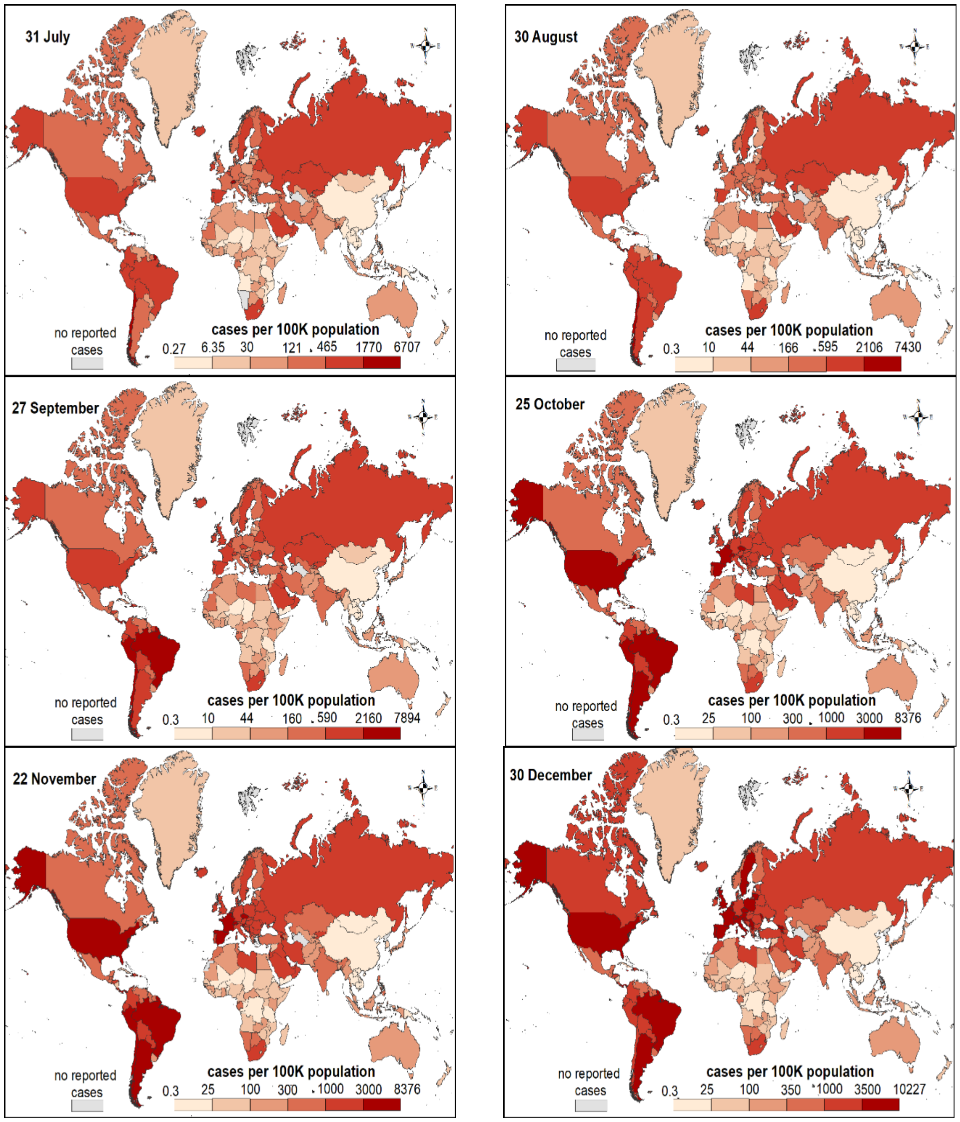

Figure 1b. Global COVID-19 crude rate per 100K population (July–December 2020).

However, in October, USA again approached in leading countries of the world with 2600 cases/100K. Apart from this, thirty-nine other countries mainly from South Americas, and Caribbean from Americas, Spain, France, Czech Republic, Belgium, Armenia, Andorra, Gibraltar, Luxemburg, Moldova, Montenegro, Netherlands, and San Marino from Europe experienced a high COVID-19 crude rate. Seventy seven countries of the world recorded high COVID-19 rate in November, which include countries from Americas, Europe, and Russia along with some from Eastern Mediterranean (Iraq, Jordan, Oman, UAE and Qatar). On the other hand, thirty seven countries from Western Pacific region and central Africa experienced as low as less than 1 to 44 cases/100K populations. End of December, revealed another high peak of COVID-19 incidence, globally affected seventy countries of the world with as high rate of >2000 cases/100K population. Most of these countries belong to Americas and Europe with 3500 cases /100K population. At the same time, Central Africa and China revealed the lowest crude rate, i.e. <20 cases/100K.

3.2 Hot Spot Analysis

Figures 2a and 2b reveal the hot and cold spots of COVID-19 incidence from 29th February to 30th December 2020. On 29th February, Western Pacific was found to be the only major hot spot of COVID-19, China being the most significant hot spot with 99% confidence level. Lai et al (2020) also reported highest daily cumulative index of COVID-19 in China during this time.

Results of March, and April, were quite significant to compare with the findings of Shariati et al (2020) for hot spot detection of COVID-19 incidence. On 31st March, COVID-19 incidence relatively decreased in China due to strict lockdown policies (Sun et al. 2020) and hot spot moved towards the Europe with high positive z-scores and significant p-values at 95% to 99% confidence level. Similar results were found for April, with Europe as a major hot spot and central Africa as a major cold spot.

In May, Europe persists to be the hot spot with 99% confidence and highest z-score followed by USA from Americas. Pakistan, Syria and Egypt from Eastern Mediterranean and Algeria from Africa also identified as hot spots with 90% confidence. China from Western Pacific region, Namibia, Zambia, Zimbabwe, Malawi, Botswana, and Madagascar from South Africa were identified as cold spot with 90% confidence and lowest z-scores values. Central African countries including Democratic Republic of Congo, Chad, Nigeria and Cameron were found to be significant cold spots with 95 to 99% confidence. Further on, the only hot spot identified in June, was South America mainly Brazil and surrounding countries with highest z-scores and 99% confidence. A study by Gomes.et al (2020) also verified that an exponential growth of COVID-19 cases occurred in northeastern parts of Brazil during this time period. Hots pot analysis of 31st July revealed several countries from Eastern Mediterranean as major hotspot along with Europe at 99% confidence level. Again, Central Africa was the only significant cold spot identified during that time.

By 30th August, significant hot spots were identified in South American countries and USA with 95 to 99% confidence level. Pakistan, Afghanistan, Kazakhstan, Iran, Iraq and Turkey were also identified as hot spots with 90 to 95% confidence level. In total 66 countries of the world were found to be significant hot spots and 65 countries from South central Africa and Western pacific region were identified as cold spots with 90 to 99% confidence level. Similar hot and cold spots were identified in September. However, October identifies Europe as a significant hot spot along with countries from Eastern Mediterranean and Americas with 90 to 99% confidence level. More than hundred countries from these regions were identified as hot spots while 73 countries from Western pacific and Africa were identified as significant cold spots with 90 to 99% confidence. Similar hot spot results were revealed during November, with 108 countries as significant hot spots and 93 countries as significant cold spots with 90 to 99% confidence level. On 30th December, 64 countries mainly from Europe, a few from Eastern Mediterranean, and Africa, and USA from America was identified hot spot with 90 to 99% confidence level, while 77 countries were identified as cold spots from Western Pacific and Africa.

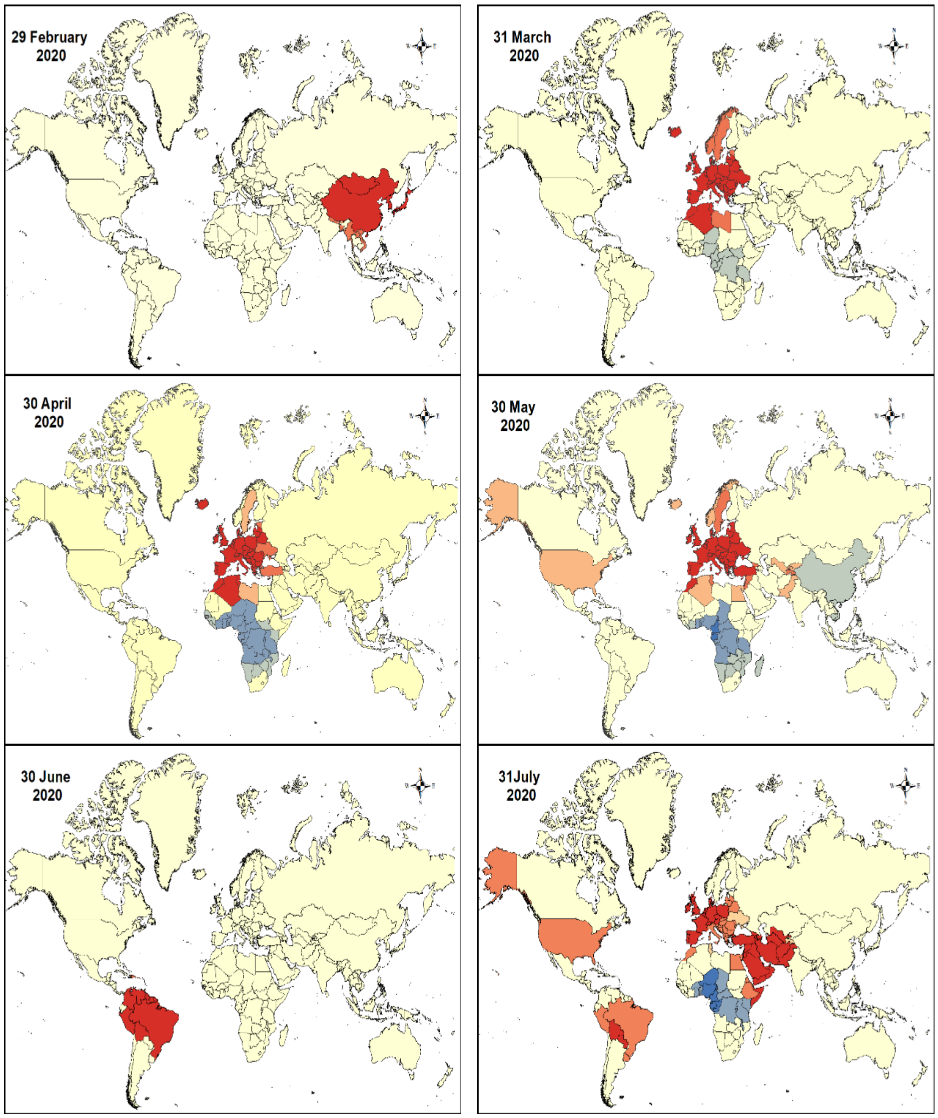

Figure 2a. Hot and cold spot detection of COVID-19 using Getis Ord G^* (February–July 2020).

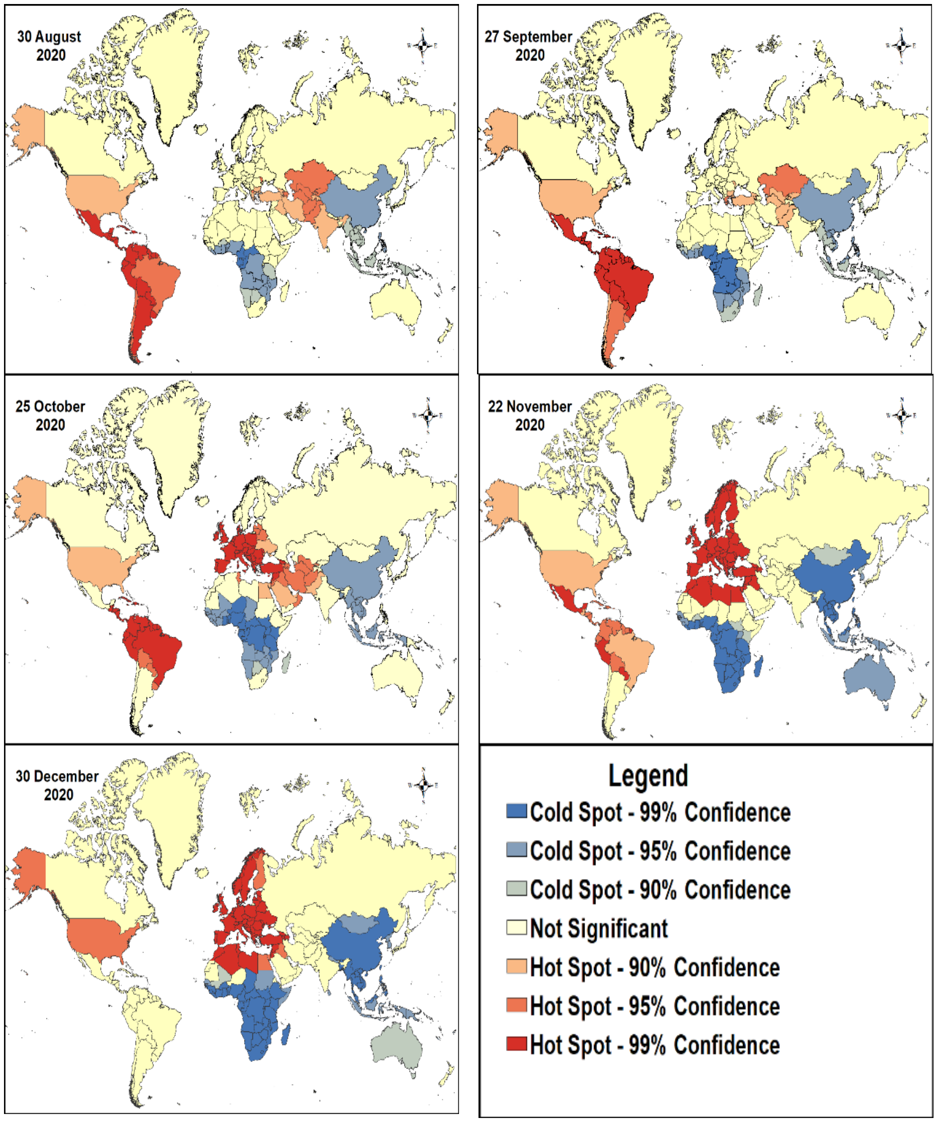

Figure 2b. Hot and cold spot detection of COVID-19 using Getis Ord *G** (August–December 2020).

3.3 Spatial Clusters and Outliers Analysis

Spatial clustering of COVID-19 through Anselin Local Moran's *I* is displayed in Figure 3a and 3b. China from Western Pacific was found to be the major High incidence cluster of COVID-19 on 29th February, while Central and South America and some countries from South Africa were identified as Low incidence clusters. By the end of March, High clusters of COVID-19 incidence shifted towards Europe. Central and South America, South and Central Africa, along with some countries from Western Pacific including China were identified as low incidence clusters of COVID-19. Low-high outliers were discovered in Eastern Europe and Northern Africa. Iran was identified as the only high low outlier because of its high COVID-19 incidence surrounded by low incidence countries. Similar clusters-outliers pattern was observed for the cumulative incidence of April, with no significant difference. However, a considerable change was witnessed in May. Europe, Canada from Americas, Saudi Arabia and Iraq from Eastern Mediterranean were identified as high incidence cluster of COVID-19. Pacific and South-Central Africa remained low incidence clusters. Gabon from Africa was the only high incidence outlier surrounded by low incidence in surrounding countries. Cluster analysis of June, showed South America as the only high incidence cluster of COVID-19.

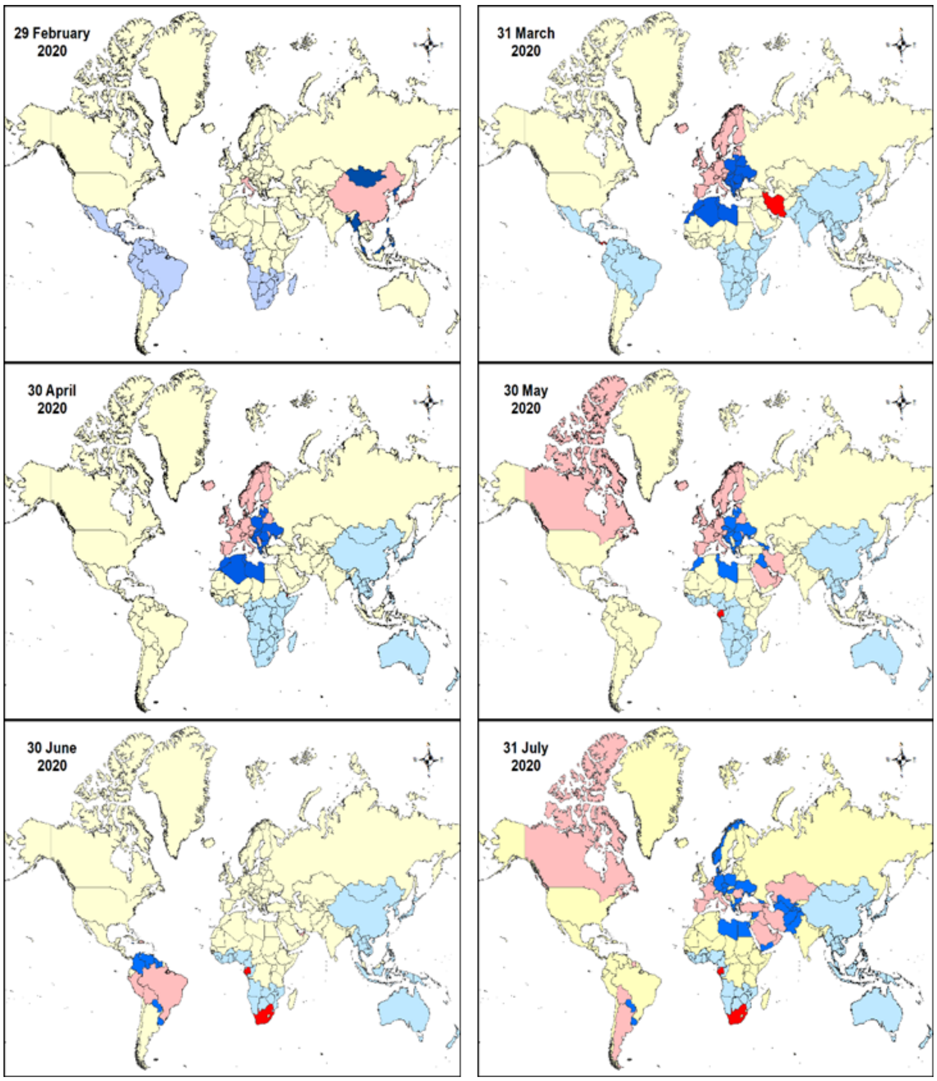

Figure 3a. Cluster and outliers of COVID-19 incidence using Anselin Local Moran's *I* (February–July 2020).

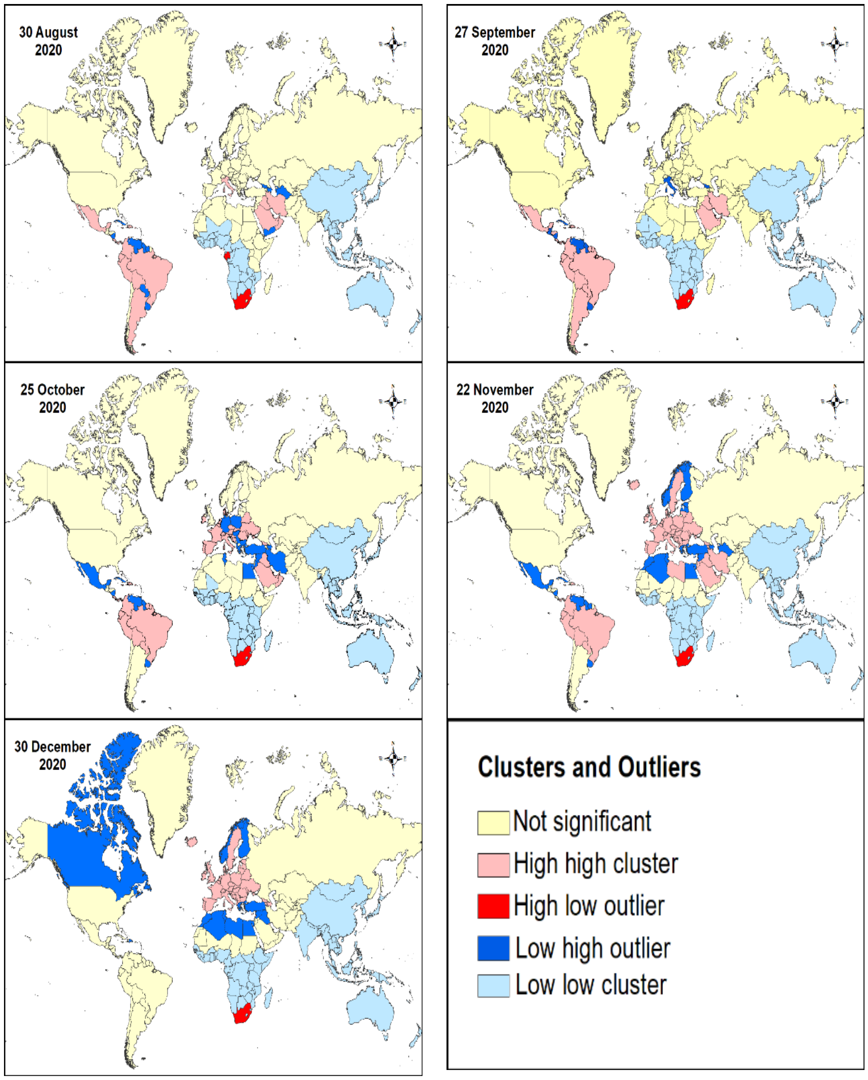

Figure 3b. Cluster and outliers of COVID-19 incidence using Anselin Local Moran's *I* (August–December 2020).

Western Pacific and South Africa were analyzed as low incidence cluster except Gabon as High-low outlier. Spatial clusters of high incidence increased in July, along addition of Europe, some Eastern Mediterranean countries, Canada, Argentina, Bolivia, Peru and Chili. Europe was not found to be the major cluster of high COVID-19 incidence during August and September, but South America and Eastern Mediterranean region were depicted in high incidence cluster group. But situation reverts again during October and November, making Europe as high incidence spatial cluster along with some Eastern Mediterranean and South American countries. It is interesting to note that between high clusters, some countries were also identified as spatial outliers with low COVID-19 incidence surrounded by high incidence countries. In contrary, South Africa was the only spatial outlier identified with high COVID-19 incidence from September to December. Results of spatial clustering of December, revealed high incidence cluster in Europe whereas, low incidence cluster in Western

Pacific. However, Low-high outliers were identified in some parts of Europe, North Africa and Canada.

3.4 Global Autocorrelation Analysis

Table 1 and Figure 4 displays the results of Global Spatial Autocorrelation analysis at a fixed distance band width of 4614 kilometers. Global spatial autocorrelation analysis of COVID-19 incidence since 30th January to 30th December results a positive Moran's *I* value greater than 0, showing significant clustered pattern. Illustrated results are based on Moran's *I* value, and z-scores (Figure 4). Moran's value of 0.01 and 0.04 associated with low z-score values of 2.1 and 2.2 in January, and February, proves less than 1% likelihood that the clustered pattern of COVID incidence could be the result of random chance. A rapid rise of 0.23 to 0.24 in Moran's *I* value and increased z-scores of 11.28 and 11.85 in March, and April, shows a significant rise in clustering pattern at a significant p-value of <0.01. However, the results of Global spatial autocorrelation in May and June lead to some spatial randomness. A decline can be noted for Moran's *I* i.e. 0.16 and z-score i.e.7.98 in May, which further falls to 0.02 and 1.85 in June. It clearly shows that spatial clustering of COVID-19 incidence falls rapidly in these two months which started to rise again in July. The second highest peak of COVID-19 incidence was observed through October to December. The increasing Moran's *I* from 0.20 in October, 0.27 in November, and 0.32 in December strongly rejects the null hypothesis of spatial randomness with p-value <0.01.

Table 1. Global spatial autocorrelation analysis of COVID-19 (January to December 2020).

Month	Moran's Index	Expected Index	Variance	Z-Score	P-value	Pattern
January	0.016944	–0.00400	0.00009	2.123	0.033	Clustered
February	0.040581	–0.00400	0.00037	2.289	0.022	Clustered
March	0.233745	–0.00400	0.00044	11.28	0.000	Clustered
April	0.244609	–0.00400	0.00044	11.85	0.000	Clustered
May	0.160163	–0.00400	0.00047	7.498	0.000	Clustered
June	0.024428	–0.00400	0.00023	1.854	0.063	Clustered
July	0.164067	–0.00400	0.00049	7.567	0.000	Clustered
August	0.158929	–0.00400	0.00046	7.599	0.000	Clustered
September	0.179963	–0.00400	0.00049	8.289	0.000	Clustered
October	0.202125	–0.00400	0.00051	9.054	0.000	Clustered
November	0.276704	–0.00400	0.00053	12.18	0.000	Clustered
December	0.328778	–0.004587	0.00056	14.05	0.000	Clustered

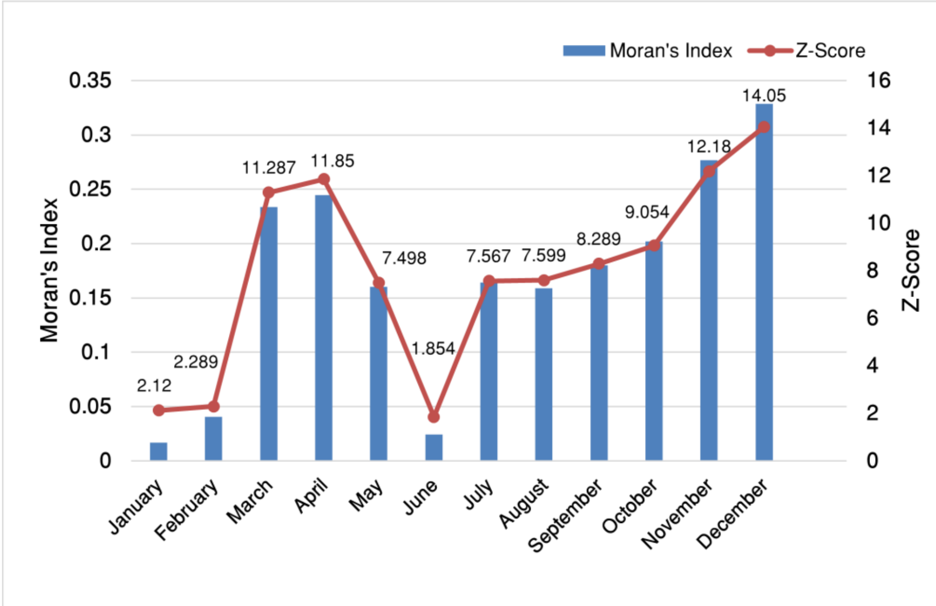

Figure 4. Global spatial autocorrelation analysis of COVID-19.

4 DISCUSSION

This study provides the initial summary of spatial distribution of COVID-19 during the year 2020. We presented global spatial distribution of COVID-19 from simple crude rates to statistically significant high and low values geographic clusters within the context of neighboring countries and against all countries in the GIS data set (Stopka et al. 2014). Results of the study revealed strong positive spatial correlation of COVID-19 incidence between neighboring countries. Altogether these outcomes provide interesting results along with the chronological changes in the pandemic.

Cluster analysis seek to locate COVID-19 clusters either high or low or outliers, but hot spot analysis served as complement to indicate the countries where COVID-19 appear different then the surrounding countries i.e. either hot spot (high incidence) or cold spot (low incidence). The COVID-19 has spread rapidly soon after its emergence in Wuhan China in late December, 2019. With the passage of time, the cluster of COVID-19 kept on moving to Europe and Americas respectively. Gayawan et al (2020) reported that Africa showed comparatively low incidence in comparison with Europe, Asia and Americas

COVID-19 crude rate maps of each month provide not only the summary of COVID-19, spatial intensity but it also provides the global propagation trend. These maps showed high rate and low rate areas, which keeps on changing throughout the year. This changing distribution pattern was driven by various factors primarily the transmission rate, risk factors, capacity of each country to deal with it and control measures taken by affected countries. Similarly autocorrelation analysis revealed moving clusters and changing hot spots temporally with some clear trends. During early2020, it was China and other Western Pacific countries which displayed as High cluster and hotspot of COVID-19, afterward they started to show decreasing trend.

Chronologically, Europe and North Africa, Americas, and Eastern Mediterranean remained hotspot for most of the months in comparison with, Western Pacific, Central and South Africa which remained cold spot for larger period of the time. Therefore, the countries which get affected in the beginning like China and South Korea were also the countries that controlled it timely. China took some serious control measures including, restriction of movement from epicenter of COVID-19 i.e. Wuhan, restrictions on travel and mass gatherings, cancellation of events, closing of institutions and wearing masks (Mackenzie et al. 2020). Similarly South Korea adopted 3T (test, track and treat) approach to minimize its outbreak clusters and control of epidemic (Kim et al. 2020). In China and North Korea, massive testing efforts have been successfully carried out. Their testing time dropped from one week to a one day, hence they control transmission. Beside testing, China contain the epidemic through quarantine, social distancing and isolation of infected people (Anderson et al. 2020). After Western Pacific, Europe was found to be the main hotspot of COVID-19 incidence through March to May. According to European Centre for Disease Prevention and Control despite of the decreasing and stable trend in most of the European Union countries, COVID-19 transmission remained widespread particularly among the aged population. In addition, one third European countries showed an increase in hospital admission due to this infection during the pandemic year. USA also maintained highest number of cases of COVID-19 despite of the control measures and medical facilities during whole year of 2020 (Andersen et al. 2021). Spatial Autocorrelation and hotspot analysis of COVID-19 incidence for the month of June, revealed least clustering pattern with South America as the only hotspot region and South Africa as the HL outlier. Least Moran's *I* value of 0.02 and lowest z-score of 1.8 also reflects some sort of spatial randomness in disease incidence in this month.

Almost all countries of South America recorded COVID-19 cases by the end of April (Kirby 2020). Uruguay and Paraguay had succeeded to control the pandemic, but Brazil and Peru were affected to greater extent during the first wave of COVID-19 and became included in high spatial clusters and hot spot region since 30th June (González-Bustamante 2021). High social vulnerability and absence of mobility restrictions are considered to be the main reasons of high COVID-19 rates in Brazil (Coelho et al. 2020).

Afterwards, by the end of July 700 million population of Eastern Mediterranean Region also came under the influence of high Covid-19 incidence. These countries showed comparatively low transmission rate till April, but mass gathering specially pilgrimages and relaxation in lockdown during May, the Holy Month of Ramadan accelerated number of cases (Al-Mandhari et al. 2020). Thus, from July to November these countries were the part of high spatial clusters and hot spots of Covid-19 incidence along with Europe and Americas.

Although strict control measures, including restrictions on Umrah, gatherings in mosques and churches, closure of educational and other institutions and even restrictions on travels also helped in slowing down the spread. WHO also gave special attention to EMR through training, monitoring and provision of testing and personal equipment (Al-Mandhari et al. 2020).

In comparison to all high spatial clusters and hot spots, Africa remained least affected by COVID-19 and emerged as low spatial cluster and cold spot of COVID-19 incidence during the whole pandemic year. Although few northern countries remained the part of hotspot during early months of the year and South Africa was identified as the only HL outlier from June to December. Makoni (2020) also reported immediate preventive measures like closure of the borders, confirmed case quarantined, and widespread curfew helped in slowing down the spread of infection in Africa. But later in September, this region showed a slight increase constituting 5% of global infection.

Among Western Pacific regions, COVID-19 incidence rate in Australia had also not been as high as China. This had been made possible by swift lockdown, shutting down of all institutions, heavy fine for not observing social distance and wearing masks, and forced quarantine for travelers returning homeland (Berger et al. 2020). Similarly New Zealand was also one of the country with lowest cases and incidence of COVID-19 among high income countries because of their intense execution of national COVID-19 control strategies (Jefferies et al. 2020).

Temporal analysis of COVID-19 incidence using global spatial autocorrelation based on Moran's *I* and z-score exposed two peaks high spatial clustering of the pandemic in the world i.e. one for the months of March-April, and the second for November-December. In contrary, Moran's *I* for the month of June, revealed least clustering of the disease reflecting a spatial randomness.

There are some limitations to our research. We use data from the single source, i.e. WHO situation reports. Spatial cluster and hots pot analysis of COVID-19 incidence were performed from the month of February as minimum 30 spatial features were required to run the analysis for significant results in GIS environment. We use cumulative COVID-19 cases for each month instead of new cases for the specific month; hence it may affect clustering results. There are many problems with the COVID-19 outbreak cases data at the international level. Examples include the problem of underreporting in low-income countries with insufficient testing facilities, the population size of asymptomatic cases in African countries with significantly lower national average age, and problems for medical service accessibility in countries with insufficient healthcare systems. Therefore, hot or cold spot analysis in a single or federal country with the same or similar healthcare systems can be significant when approached from a policy perspective. However, approaching based on macroscopic global statistics rather than microscopic data can significantly distort results due to age standardization problems and the population size problem of asymptomatic cases. In addition, we did not compare mortality and recovery rates with incidence rate of COVID-19.

Notwithstanding these limitations, our study provides a meaningful backdated analysis about spatial diffusion or transmission of COVID-19 incidence during all months of the pandemic year 2020 at global level. Thus, study will provide a baseline approach for epidemiologists to examine the causes of COVID-19 transmission for future research. Moreover, it helps the countries to revise and enhance the pharmaceutical and non-pharmaceutical policies and interventions to break the chain of spatial clusters of COVID-19 in forthcoming year. Currently in 2021, because of the emergence of new variants and vaccine development and its provision, the spatial pattern of COVID-19 incidence is quite different than 2020. Some of the countries like China, North Korea did not experience second wave, however other countries, for example India presently showing the high incidence as second wave. Thus, this study provokes new research questions and provides the base for the up forth comparative spatial research with the successive years and also among different regions and countries.

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