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The Impact of Human Mobility of COVID-19 Epidemic in Kuala Lumpur using GIS

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ABSTRACT

During the third COVID-19 wave in Malaysia, the Ministry of Health suggested a complete lockdown (Movement Control Order-MCO). However, tracking people's movements would help curb the virus' spread. Movement data helps companies uncover human mobility patterns, analyse present and previous movement patterns, and anticipate future consequences. GIS can generate flow maps, themed maps, and flow charts. GIS can show people moving from one site to another and study the link between people moving and land usage. This work utilised GIS to predict and construct lockdown zones based on human mobility. Between November and December 2020, it was also used to tour the most popular places. A survey of 380 Malaysians was undertaken. At the same time, Mysejahtera apps provided data on people's movements. This research was done in Kuala Lumpur and the respondents' data was arranged into an excel document. Then, the GIS programme simulated human activity and plotted regions with a "likely increase in ratio/speed of infection." Between November and December 2020 (RMCO time), everyday movements of Kuala Lumpur people might be utilised to apply "restrictive measures for COVID-19 containment". Instead of a nationwide lockdown, these locations should be targeted for localised lockdowns. So, the government should concentrate on a smart lockdown strategy to prevent catastrophic economic devastation. This research also helped health authorities and governments minimise mobility by optimising the allocation of the most frequented areas concerning population density. This method helped control the pandemic more efficiently and scientifically.

INTRODUCTION

Health Director-General Tan Sri Dr. Noor Hisham Abdullah, the former Malaysian Ministry of Health (MOH) On the 10th of October 2020 announced that Malaysia was entering the third wave of the COVID-19 pandemic(Noor Hisham Abdullah | DNDi, 2021). He was worried that the movement of six million people in the Klang Valley and Negeri Sembilan would contribute to a further increase of COVID-19 cases in the respective States i.e. Selangor, Federal Territory of Kuala Lumpur, and Negeri Sembilan. Klang Valley is an urban conglomeration in Malaysia whereas Negeri Sembilan is a state lying on the western coast of Peninsular Malaysia. He cautioned that nearly all the districts in Selangor, Kuala Lumpur, and Putrajaya were then COVID-19 red zones and that it would be difficult to control the movements of people in those densely populated States should the epidemic spreads. The COVID-19 cases started to increase significantly in Malaysia from October 2020 to 7 February 2021 reaching 242,452 cases (in Malaysia) and 7959 cases (in Kuala Lumpur) respectively (Figure 1 and Figure 1-1). Indeed, this turbulent increase is a reflection of the people's movements during those periods of the year which will be discussed further in this article. Discussions take off in defining areas under study. Then the study will explore the most visited venues during the period between November and December of 2020. Finally, the study will propose lockdown boundaries and zones based on the people's movement patterns in an effort to curb the spread of the epidemic.

Considering official data and good projections are still sparse this research had to depend on digital data sources, such as data from mobile phones and other digital devices to track the breakouts induced by newly found pathogens (Ienca & Vayena, 2020). Furthermore, studies demonstrated the feasibility of anticipating the development of the COVID-19 epidemic by merging data from the Official Aviation Guide with data on human movement from Tencent's WeChat app and other electronic services (Ienca & Vayena, 2020). Interestingly, data of the mobile-phone had already shown its predictive capability, for instance, in anticipating the geographical spread of cholera in 2010 (Bengtsson et al., 2015). Additionally, the Haiti cholera pandemic demonstrated the efficiency of big data analytics during the 2014–2016 Western African Ebola outbreak (GHRF Commission (Commission on a Global Health Risk Framework for the Future), 2016). When it comes to the methods and tactics that are being used to examine the current epidemic, spatial analysis is becoming more popular for studying the effects of COVID-19. Spatial-temporal approaches have been used extensively to investigate lockdowns and the changes in human movement that result from them. One of the most well-investigated topics has been the interaction between pollution and COVID-19 dynamics, which has been shown to increase human activities' influence on the pandemic's development (Franch-Pardo et al., 2021).

Hence, this study attempted to prove the importance and influence of Geographic Information Systems (GIS) in

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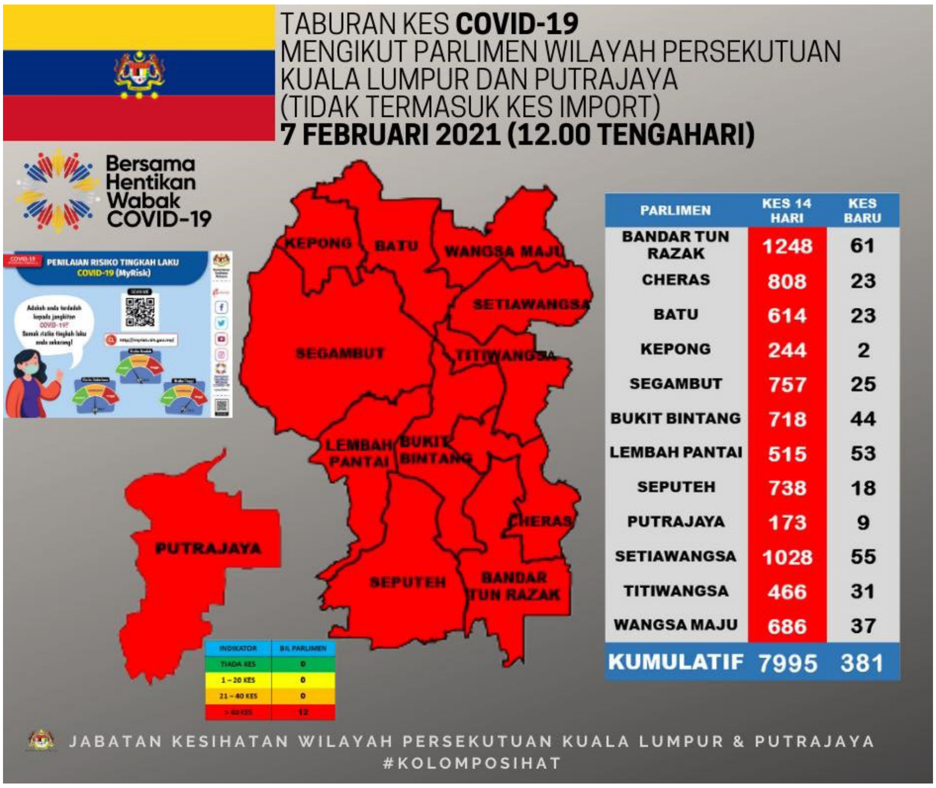


Figure 1:. Kuala Lumpur cases by districts as of 7 February 2021.

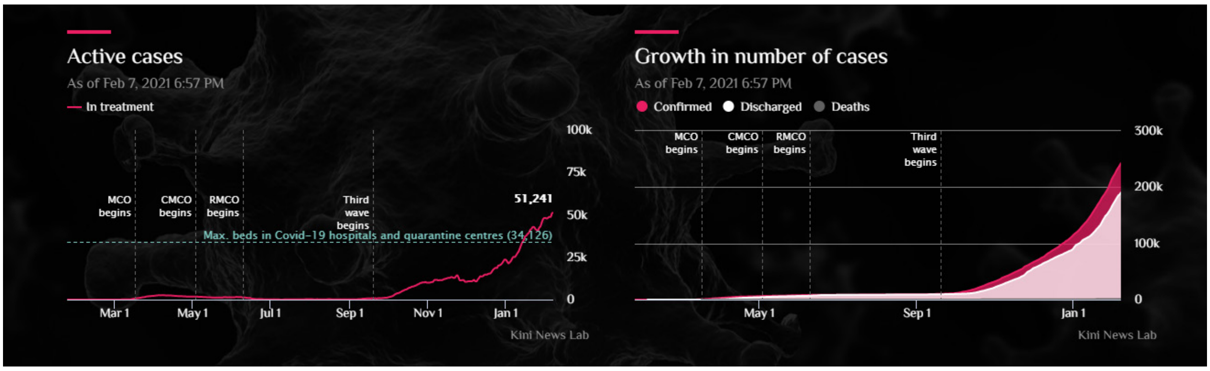


Figure 2: Malaysia covid -19 cases as per 7 February 2021 data.

tracking the daily movements of people in relation to land use distribution. This study produced three results. To begin, it demonstrated the effect of the COVID-19 epidemic's propagation, and, secondly, it established and was capable of establishing lockdown limits and zones depending on human mobility. Lastly, it simulated the most visited areas during the period between November and December of 2020.

LITERATURE REVIEW

Since COVID-19 is the most recent pandemic that has inflicted on the whole world, there are still a few studies on this matter. Furthermore, studies focusing on the movement of people and its relationship to the pandemic are mostly theoretical focusing mainly on how to achieve social distancing. However, studies on practical matters such as people movement analysis to determine the lockdown places are still lacking. The applicability and usefulness of mobile GIS as a human movement data collection tool were examined. The research area was chosen to be the premises of the University of Moratuwa. In comparison to other approaches, the study found that the mobile GIS method offered excellent efficiency, accuracy, and reliability as a data-gathering method for human mobility (Bandara et al., 2014). For this study, individual tracks have been collected via email. Respondents of this study comprised only students at the International Islamic University Malaysia (IIUM) and they were taken as the sample. The sample size has been derived based on the student distribution among the Kulliyyahs and the Departments. The sample size was in proportion to the number of students in the departments. Then key attributes have been derived by using collected tracks. The efficiency/reliability and accuracy of data collection and analysis were then assessed. The analysis has been done by using GIS software packages specifically the ArcGIS software. Individual tracks have been recorded by using free and open-source applications. In this study, the My

Tracks (android app) app has been used.
Wildlife biologists use telemetry instruments (such as bio-logging GPS tags) to trace the movements of animals. The trajectories of the animals are then combined with contextual information about the environment, such as data gathered by remote sensing. A relatively recent study in the science of ecology, movement ecology explores the Spatio-temporal patterns and processes that underpin animal movement in both the wild and the laboratory (Ossi et al., 2021). To minimize contact rates and avoid the transmission of COVID-19, it is essential to restrict movement as much as possible (Vannoni et al., 2020). The imposition of lockdown limitations resulted in a significant decrease in human mobility (Madden et al., 2021),

Meanwhile, other experts have done comparable mobility studies to ascertain where pet cats travel while they are outdoors. Scientists have attempted to address this subject previously, either by tracking cats on foot or by collaring cats with radio transmitters, but Cat Tracker proved unique in its scope. (Jonathan Losos, 2020). Nearly a thousand cats across four countries wore GPS trackers for a week to shed light on how far they travelled and where they went. After six years, the results came in. A report was published in the Animal Conservation Journal, where the Cat Tracker team compiled data across continents and found that for most cats, there is no place like home (Jonathan Losos, 2020).

An approach to extracting information from large Origin-Destination (O-D) mobility data was introduced to a new approach to the discovery and understanding of Spatio-temporal patterns of movements (Guo et al., 2012). According to them, features extracted from complex interconnections between a significant number of point locations should include two steps:
(1) spatial clustering of massive GPS points to identify potentially constructive locations; and (2) extracting and mapping out cluster flow measures to understand the spatial distribution and temporal trends of movements. Another example study illustrating and validating the concept uses a huge dataset of taxi itineraries in Shenzhen, China. Exceptionally, such research makes a dual contribution. To begin, it introduces a novel approach for recognising spatial structures and location patterns contained in O-D motions. Second, the technique is scalable to big data sets and is capable of synthesizing enormous amounts of data to aid with pattern extraction and comprehension. Simultaneously, several patterns in the taxi data have been uncovered, some of which corroborate prior information about city planning principles and standards.

Data from social media was evaluated and used to uncover patterns that could help smart city planners make better decisions. They tracked citizen movement behavior using Weibo social media data to study social-geographic human mobility in Shanghai's Central Business District (CBD). The goal was to see if geo-located Weibo data could be used to find out about human mobility and activity patterns. It intended also to use location-based services to identify crucial areas in people's life. They applied some algorithms, and the findings were displayed using appropriate visualization approaches to show the human mobility patterns discovered utilizing large-scale social media data. The findings back up smart city planning decision-making concepts (Ebrahimpour et al., 2020).

The potential of smartphone data for assessing movement and social contact was examined. The potential of smartphone data for assessing movement and social contact was examined (Couture et al., 2020). These data covered a sizable portion of the US population and demonstrated similar migration patterns to those observed in conventional survey data. They created and distributed a public index of location exposure that described county-to-county migration (Pope, 2020). These indices are intended to quantify the variation in activity reductions caused by pandemics across individuals and locations. The county-to-county LEX was used to obtain migration details for that investigation. As a result, the LEX reported a sharp reduction in travel between New York County and neighboring counties from March 2020 to April 2020.

MATERIALS AND METHODS

There are four unique approaches to descriptive and causal research. They consist of a research survey (primary research), experimentation, a study using secondary data, and observational data (Zikmund, 2003). At the same time, there is no hard and fast rule for selecting the optimal research design. It is entirely depending on the research objective and setting (Zikmund, 2003). As a result, this study collected primary data through survey and questionnaire approaches. The measures were taken in this study's methodology.

Problem detection

- How are the peoples' movement patterns in Kuala Lumpur city?
- What are the purposes of peoples' movements in Kuala Lumpur city?
- What are the relationships between movements and the COVID -19 cases?

Data collection

The total sample for this research was determined using two corresponding methodologies, namely, i) a priori G*Power analysis (Karpov et al., 2010) (El Maniani et al., 2016), and ii) sampling table (Robert V. Krejcie, 1970). The G*Power analysis can discard the null hypothesis when it should be rejected (Mccrum-Gardner, 2010). Principally, G*Power analysis is needed for sample size determination when using PLS-SEM (Christian M. Ringle, 2014). Whereas, (Robert V. Krejcie, 1970) sampling table is the commonly used approach for sample size determination in social sciences and behavioural studies (Sekaran & Bougie, 2005). The sampling table offers the sample size estimation based on the study population.

Data Processing

This section outlines the critical processes and methods used to analyze the data being collected. Multiple Regression Analysis is used to address the defined research questions. However, Multivariate Analysis requires the fulfilment of specific conditions before the analysis. As a consequence, the multivariate assumption tests listed below were conducted. They are Missing Values Assessment, Outliers Assessment, Normality Assessment, and Multicollinearity Assessment.

Data collection

The researcher for this study used a primary survey since there was a shortage of online data and because people's movements are considered to be private information. A cross-sectional survey was carried out between November 2020 and December 2020 during the Recovery Movement Control Order (RMCO), which was in effect at the time. The survey's intended sample size is 380 participants. The Mysejahtera apps, which were developed by the Malaysian Ministry of Health and made available to the public, provided information on people's movements. Table 1

Table 1: Data collection from various locations in Kuala Lumpur City

Resident Name in Malaysia	Area	Number of Sample
Mcity Resident	Titiwangsa	17
Pv 8 Resident	Batu	55
Royal Regent Resident	Titiwangsa	24
Danau Kota Resident	Wangsa Maju	29
Setapak Jaya Resident	Wangsa Maju	35
Wangsa Delima	Wangsa Maju	32
Maluri Resident	Titiwangsa	32
Taman Shamelin Perkasa Resident	Titiwangsa	41
Taman Koperasi Fasa	Batu	30
Suria Jelatek Residence	Titiwangsa	46
Lingkaran Syed Putra Resident	Bukit Bintang	39
	Total =	380

illustrates the split of the data by geographic region and the number of respondents who took part in the poll. Figure 2 shows an example of how Mysejahtera Apps illustrate information about population movements.

Daily COVID-19 cases data were obtained from 31st December to 13 January 2021 from the Health Department of Kuala Lumpur & Putrajaya (Figure 3).

The georeferencing of certain raster data is required for the majority of GIS applications. Geographically referenced raster data is created by giving real-world coordinates to each of the raster's pixels. These coordinates are gathered by field surveys in which coordinates are collected using a GPS device on specific distinguishable features in the picture are recorded. Meanwhile, the maps downloaded from the websites were updated for Geo-referencing purposes using the ArcGIS programme, which was used to turn the digital maps into a format that could be used for research.

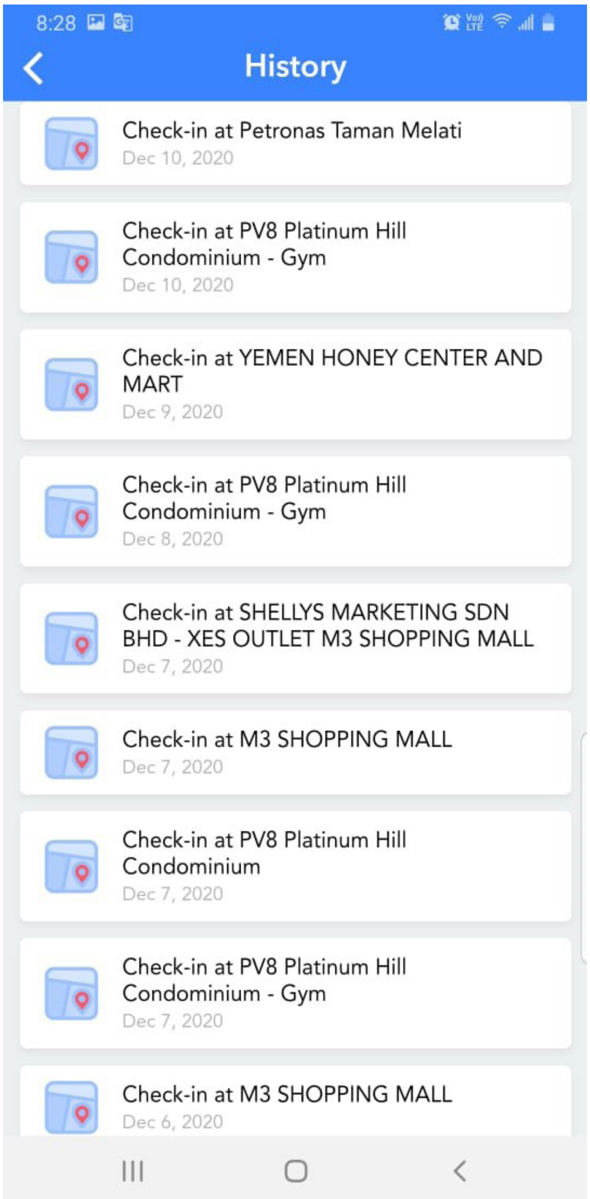


Figure 3: Sample of Mysejahtera apps (this screenshot of the mobile apps was taken in January 2020).

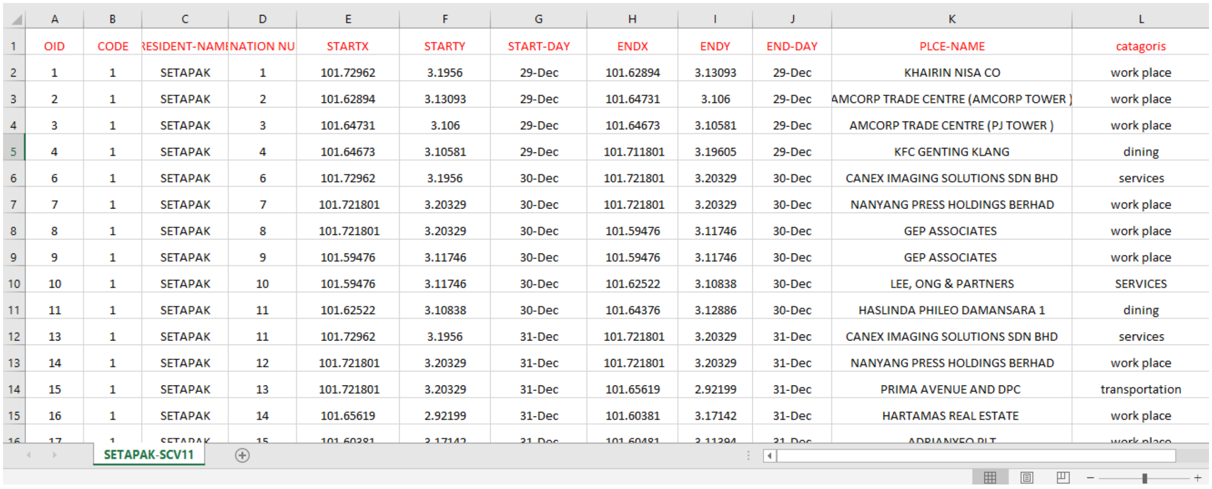
The data of the 380 respondents obtained from MySejahtera apps was screenshot, organized, and classified using Microsoft Office Excel as shown in Figure 5 below.

Kuala Lumpur residents' Trajectory Data

The traces of the 380 respondents were included in the human movement data set that was utilised for the research. Their locations were recorded for two months (November and December 2020). A location map recorded the O-D of each respondent. In other words, the Trajectory data was captured. In this research, a trajectory refers to a person's journey from the point of origin to the point of destination.

There was a total of 10780 trajectories (trips) and 6697 locations (GPS points). Each trajectory had a start and an end time. Nevertheless, Of course, it is neither possible nor meaningful to display all of the O-D links

Figure 4: The COVID-19 data from the Malaysian Ministry of Health official web.



	A	B	C	D	E	F	G	H	I	J	K	L
1	OID	CODE	RESIDENT-NAME	NATION NU	STARTX	STARTY	START-DAY	ENDX	ENDY	END-DAY	PLCE-NAME	catagoris
2	1	1	SETAPAK	1	101.72962	3.1956	29-Dec	101.62894	3.13093	29-Dec	KHAIRIN NISA CO	work place
3	2	1	SETAPAK	2	101.62894	3.13093	29-Dec	101.64731	3.106	29-Dec	AMCORP TRADE CENTRE (AMCORP TOWER)	work place
4	3	1	SETAPAK	3	101.64731	3.106	29-Dec	101.64673	3.10581	29-Dec	AMCORP TRADE CENTRE (PJ TOWER)	work place
5	4	1	SETAPAK	4	101.64673	3.10581	29-Dec	101.711801	3.19605	29-Dec	KFC GENTING KLANG	dining
6	6	1	SETAPAK	6	101.72962	3.1956	30-Dec	101.721801	3.20329	30-Dec	CANEX IMAGING SOLUTIONS SDN BHD	services
7	7	1	SETAPAK	7	101.721801	3.20329	30-Dec	101.721801	3.20329	30-Dec	NANYANG PRESS HOLDINGS BERHAD	work place
8	8	1	SETAPAK	8	101.721801	3.20329	30-Dec	101.59476	3.11746	30-Dec	GEP ASSOCIATES	work place
9	9	1	SETAPAK	9	101.59476	3.11746	30-Dec	101.59476	3.11746	30-Dec	GEP ASSOCIATES	work place
10	10	1	SETAPAK	10	101.59476	3.11746	30-Dec	101.62522	3.10838	30-Dec	LEE, ONG & PARTNERS	SERVICES
11	11	1	SETAPAK	11	101.62522	3.10838	30-Dec	101.64376	3.12886	30-Dec	HASLINDA PHILEO DAMANSARA 1	dining
12	13	1	SETAPAK	11	101.72962	3.1956	31-Dec	101.721801	3.20329	31-Dec	CANEX IMAGING SOLUTIONS SDN BHD	services
13	14	1	SETAPAK	12	101.721801	3.20329	31-Dec	101.721801	3.20329	31-Dec	NANYANG PRESS HOLDINGS BERHAD	work place
14	15	1	SETAPAK	13	101.721801	3.20329	31-Dec	101.65619	2.92199	31-Dec	PRIMA AVENUE AND DPC	transportation
15	16	1	SETAPAK	14	101.65619	2.92199	31-Dec	101.60381	3.17142	31-Dec	HARTAMAS REAL ESTATE	work place

SETAPAK-SCV11

Figure 5: While the MySejahtera apps showed the date of a person movement, this study used the O-D tracking to detect the starting point of the respondents., For the daily movements, a specific code for each movement of each person was given.

on the map, as doing so would result in a cluttered and illegible display. To sift through the huge data and identify intriguing patterns and structures, the data were filtered by removing duplicate points and clipped into the research area layer, which served as a starting point for this investigation (in this case, Kuala Lumpur City). Finally, a total of 5682 trajectories (trips) and 3255 locations (GPS points) remained after the data was filtered (See Figure 6). As regards the Points of Interest (POI) activities, the POI data was classified into nine different categories as follows:

1. Dining Outlets (Restaurants, Cafes, Food Courts, And Tea Houses),
2. Petrol Stations,
3. Shopping Malls,
4. Workplaces (Offices, Companies, Industrial Areas, And Banks),
5. Healthcare (Sports Centres, Hospitals, Clinics),
6. Entertainment (Ktvs, Parks, Cinemas, Museums, Temples, Concert Halls, And Art Galleries),

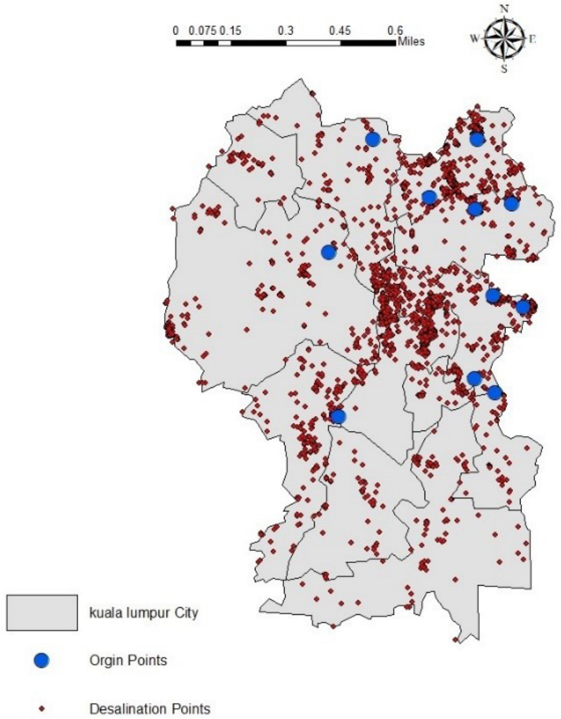


Figure 6: Filtered O-D Data for Kuala Lumpur

7. Social Services (Beauty Salons, Hotels, Post Offices, Stores, And Supermarkets),

8. Education Centres (Universities, Kindergartens, Libraries, Institutes),

9. Transportation (Bus Stations, Train Stations, Airports, Mass Rapid Transit (Mrt), And Light Rail Transit (LRT) Stations.

RESULTS AND DISCUSSION

Spatial Discovery and Analysis: Analysis of the Most Visited POI

The statistical results shown in Table 3 reveal that the Shopping malls category attracted the greatest number of visitors with a percentage of 31% followed by the social services category at 24.8% and dining outlets at 24%. The least number of visits was to petrol stations (0.8%).

Figure 7 shows the concentration of each category of POI in each district of the City of Kuala Lumpur and shows the distribution of visited POI during the RMCO period. The most visited POI were located in Bukit Bintang, Titiwangsa and Setiawangsa districts.

Table3: Distribution of POI by category

CATEGORY	NUMBER OF CHECK-IN	PERCENTAGE
Dining	689	21.1%
Education	17	0.5%
Entertainment	78	2.3%
Workplace	344	10.5%
Service	808	24.8%
Transportation	125	3.8%
healthcare	101	3.1%
Shopping mall	1011	31%
Petrol station	24	0.7%

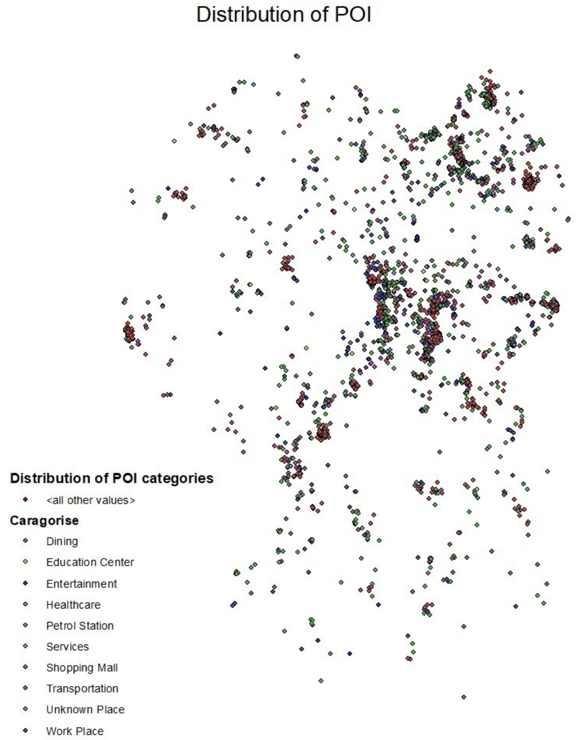


Figure 7: The distribution of POIs by category during the RMCO period.

This coincided with the high cases recorded for COVID-19 cases from December 1(except for 15 and 26 December) to January 15, 2021 (See Figure 8). Unfortunately, the conditions and rules for public movement did not change during this period which suggests that the RMCO was ineffective in curbing the spread of the epidemic. Therefore, this study believes that it is imperative to review the Standard Operating Procedures (SOP) for public movement during RMCO periods.

Analysis of the Flow Maps of Public Movement

Generally, Flow Maps show the movement of some phenomenon, normally goods or people, from one place to another. Lines are used to symbolizing the flow and at the same time are typically varied in width to represent differences in the quantity of the flow. In this study, the endpoint coordinates were converted into lines that showed people's movements. However, some other flows diffused from their origins to multiple destinations.

Kuala Lumpur respondents' movement was sourced from eleven resident apartments in Kuala Lumpur as shown in Figure 9. This Mobility Flow Map shows that most of them are headed towards the centre of the city, which is the Bukit Bintang district. The reason for this is that most services are located in that area, especially shopping malls and dining outlets which made the area attract the largest number of people, and which proportionately led to the increase in COVID-19 cases there during the RMCO period.

An analysis was done on the COVID-19 cases in Kuala Lumpur City from 1 December to 15 January 2021 (Table 4).

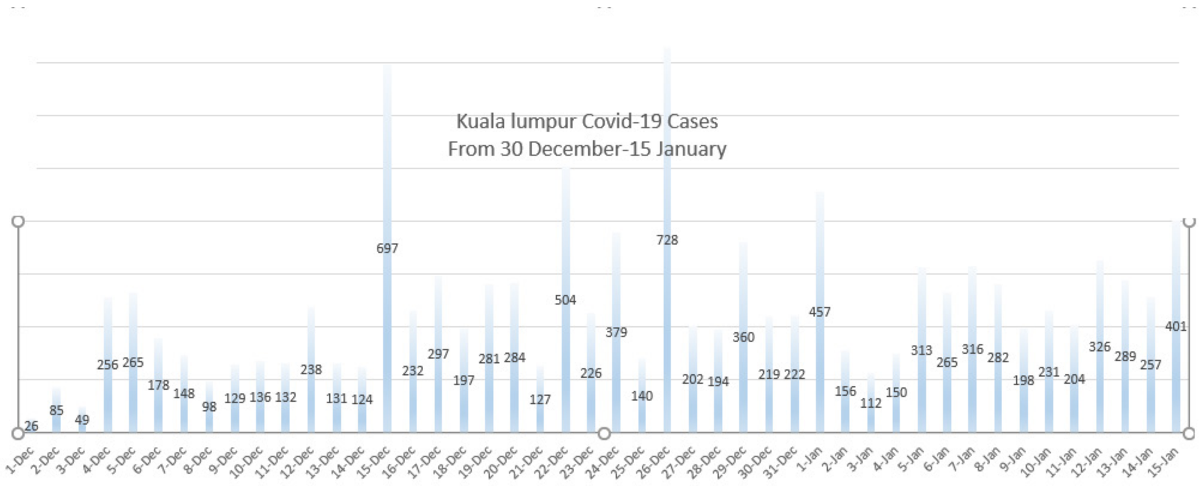


Figure 8: The Kuala Lumpur public movements from 1 December to 15 January 2021.

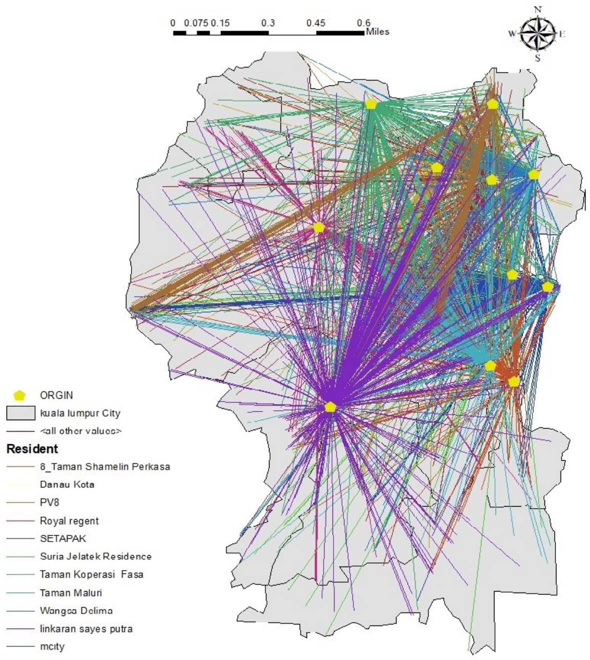


Figure 9: The Mobility Flow Map of 11 locations in Kuala Lumpur city.

A total of 9799 cases were recorded in Kuala Lumpur City between December 1 and January 15, 2021, and Bukit Bintang districts recorded the largest number of cases with 3555 at 36.2% while the lowest was in Kepong with 211 (2.1%) cases only. Figure 10 is a Bar Chart comparing the highest and the lowest cases of the eleven districts of Kuala Lumpur City during the period under study.

Segambut district recorded the second-highest rate of COVID-19 cases. Unfortunately, this has been ignored because the movement data collected was from the north of the city while the areas worse inflicted were at the centre and eastern side of the city. Hence, in the future Mobility Flow Maps should be able to facilitate the government to mobilise resources at the appropriate locations.

The mean centre of the visited places (POI) concentrated in the Bukit Bintang area, and therefore the area represents the Centre of attraction of the districts or the geographical centre of the concentration.

Figure 11 shows the number of POI within the standard distance of 2182 POI which is 67%. This indicates that the visited places were regularly distributed and had a tendency towards clustering because it was supposed to include the circles i.e. at 68.2%. The apparent elements

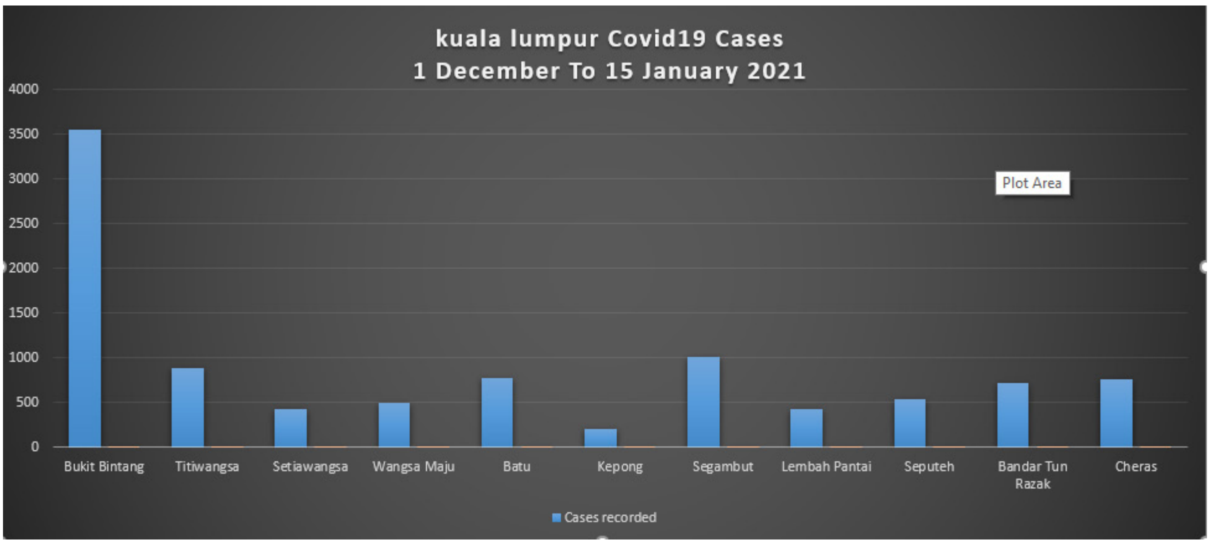


Figure 10: Kuala Lumpur City COVID-19 cases by Districts.

Districts	Cases recorded	percentage
Bukit Bintang	3555	36.2%
Titiwangsa	884	9.0%
Setiawangsa	424	4.3%
Wangsa Maju	502	5.1%
Batu	772	7.8%
Kepong	211	2.1%
Segambut	1015	10.3%
Lembah Pantai	425	4.3%
Seputeh	538	5.4%
Bandar Tun Razak	716	7.3%
Cheras	757	7.7%
Total	9799	100%

Figure 10: Kuala Lumpur City COVID-19 cases from December 1 and January 15, 2021

were found to be regularly distributed and the ratio was roughly the same as the standard distance related to the positive correlation with the dispersed distribution. This explains the increased value of standard distance than the average centre, increased contrast, and dispersion of the features. The higher the concentration of features, the smaller the standard distance which directly shows the nature of the spatial distribution of POI in Kuala Lumpur City.

5. The pattern of the spatial distribution of visited venues in Kuala Lumpur City was further analyzed in terms of 1) the Average Nearest Neighbour, 2) the

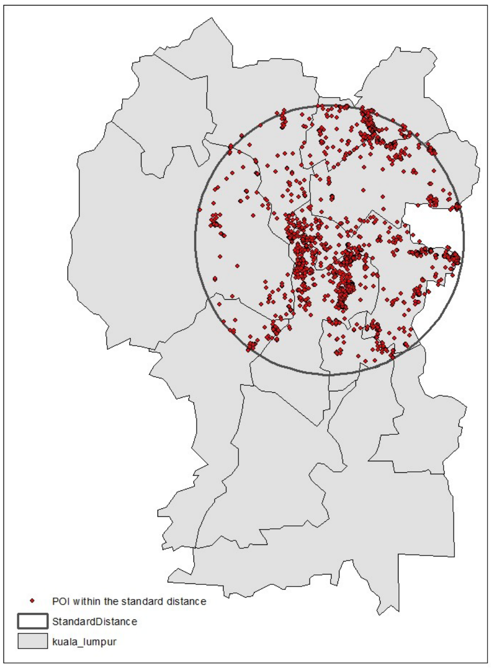


Figure 11: The Spatial Distribution of POI in Kuala Lumpur City.

Moran I Analysis and 3) the Kernel density of POI.

5-1 The Average Nearest Neighbor

The first analysis used on the data was the Average Nearest Neighbour. The primary purpose of this analysis is to determine the distribution of visited venues to see if the spatial orientation of the data is dispersed (i.e. approximately equally distributed across an area), random, or clustered.

Figure 12 shows the output report of the Nearest Neighbour tool. It can be seen that the Nearest Neighbour Ratio is approximately 0.38 which is a bit less than one.

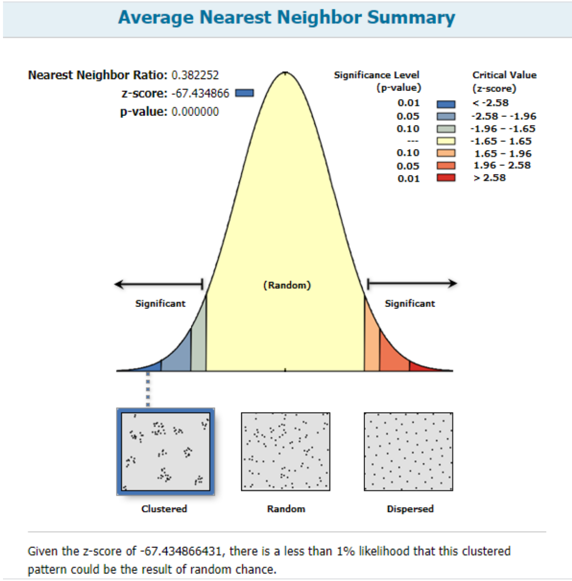


Figure 12: The POI Average Nearest Neighbour

Therefore, it can be concluded that the data is not randomly distributed but is either clustered or dispersed. Then the z-score was used to gauge the critical values provided in the output. It is seen that the z-score of 67 puts the data in the left tail of the normal distribution (i.e. < -2.58) which is considered clustered. The results also indicate that there is a very small likelihood that the clustering is the result of a random chance.

The Moran I Analysis

The Spatial Autocorrelation or Global Moran I Analysis tool measures spatial autocorrelation based on both feature locations and feature values simultaneously. Given a set of features and the associated attributes, it evaluates whether the pattern expressed is clustered, dispersed, or random. The tool calculates the Moran's I Index value and both the z-score and p-values(How Spatial Autocorrelation (Global Moran's I) Works—ArcGIS Pro Documentation, n.d.).

The results of the spatial Autocorrelation tool (Figure 12) suggest that the pattern of POI at each feature location is clustered. The Moran's Index was 0.346961; the z-score was 33.38. The critical value (z-score) was less than 2.58 but greater than 1.96 thus suggesting that there is less than 1-percent likelihood that the clustered pattern is a result of a random chance.

The Kernel Density of POI

Kernel Density is a statistical method that calculates the magnitude-per-unit area from the point or polyline features using the Kernel function to fit a smoothly tapered surface to each point or polyline.

Figure 14: The density of the visited venues (POI) in the

study area was calculated by calculating the density of POI around the centre point. The value was higher at the centre and decreased by moving away from it. Figure 12 shows the density of POI in each zone i.e. High density and Low-density areas. It highlights the different grades of the POI density in Kuala Lumpur City areas that gradually shows the high to low densities. This analysis

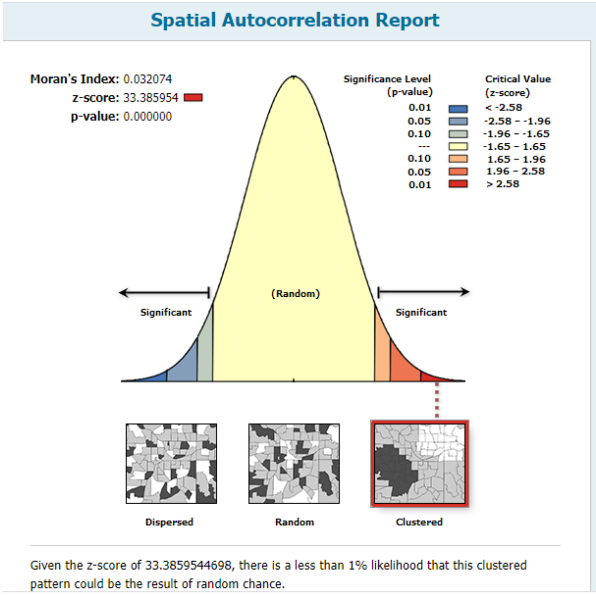
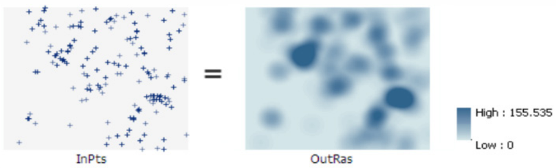


Figure 13: The Moran I Analysis



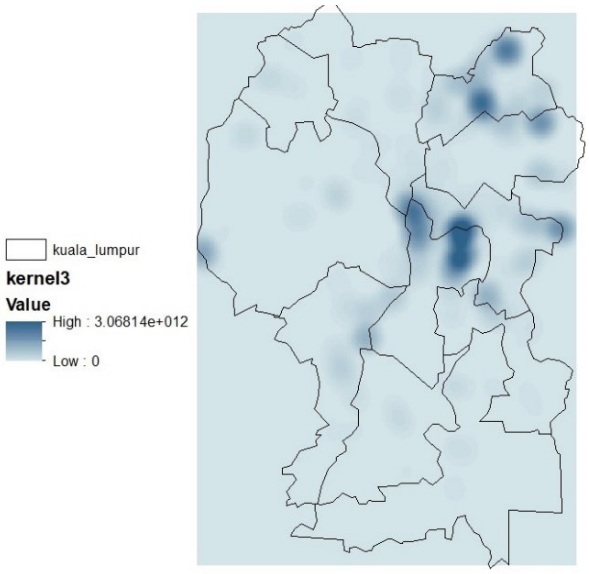


Figure 14: The Kernel Density Map of POIs of Kuala Lumpur City.

also confirms the results of previous analyzes that all points were highly skewed spatially.

Hotspot Analysis and Creating Smart Lockdown Areas

A hotspot can be described as a location where there is a higher concentration of activities than would be expected if the activities were distributed randomly. The study of point distributions or spatial configurations of points in space led to the development of hotspot detection techniques (Sanjoy Chakravorty, 1995). A complete spatial randomness model, which describes a process in which point activities occur completely at random, such as the Homogeneous Spatial Poisson Process, is used when investigating point patterns because the concentration of points inside a defined area is tried to compare to the density of focuses within a defined area Beyond determining the density of points in a given area, the Hotspot Technique measures the degree to which point activities interact with one another to comprehend their spatial relationships (Hot Spot Spatial Analysis | Columbia Public Health, n.d.). Following that, using this approach, this research will discover and decide the locations that need to be locked down in order to protect the public.

Optimized Hot Spot Analysis Analyses

The Optimized Hotspot Process was used in this study to determine the areas of the most visited venues, which simultaneously recorded the highest cases of COVID-19 in the period from 1 December to 15 January 2021. The first step of the analyses was to optimize hotspot venues by Integrating the POI in three iterations. The first iteration was by using the adjusted snap distance times of 0.10, then by using the adjusted snap distance times of 0.25, and finally by integrating with a snap distance equal to the fully adjusted snap distance. Performing the integrated steps in three phases minimized distortion of the original point locations. However, there was a collapse of the snapped points yielding into a single point at each location with a weight to visited venues (POI) and the numbers of visits (POI) snapping together. This part of the aggregation process was resolved via the Collect Events Method. The last component of the Optimized Hot Spot Analysis tool is to create the Output Features whereby the Input Features represent the most visited venues (POI) of the city(How Spatial Autocorrelation (Global Moran's I) Works—ArcGIS Pro | Documentation, n.d.). The output features reflect the aggregated weighted features (Polygons for Aggregating POI into Points parameter) (How Spatial Autocorrelation (Global Moran's I) Works—ArcGIS Pro | Documentation, n.d.). Each feature will have a z-score, p-value, Gi Bin result, and the number of neighbours each feature was also included in their calculations. Figure 15 shows the Optimized Hot Spot Analysis workflow.

The final output of the Optimized Hotspot Analysis is a map that identifies the risk areas that are supposed to be the Lockdown Area. Figure 15 shows the Lockdown Area comprising of the Bukit Bintang, Titiwangsa and Setiawangsa Districts. These were declared as the Red Zone areas due to their record high COVID-19 cases.

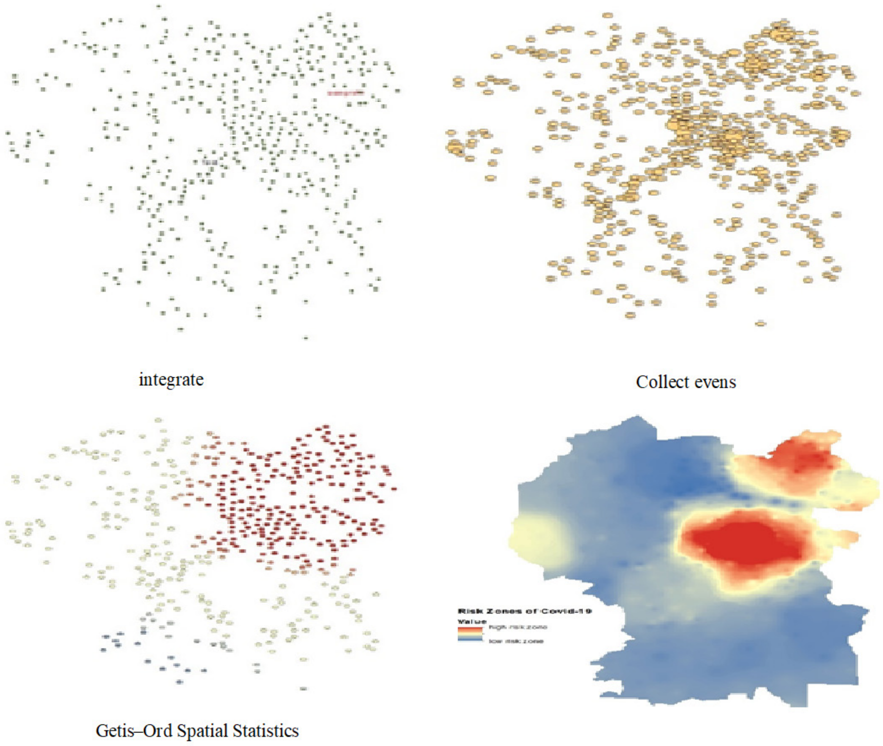


Figure 15-1: Optimized Hot Spot Analysis workflow

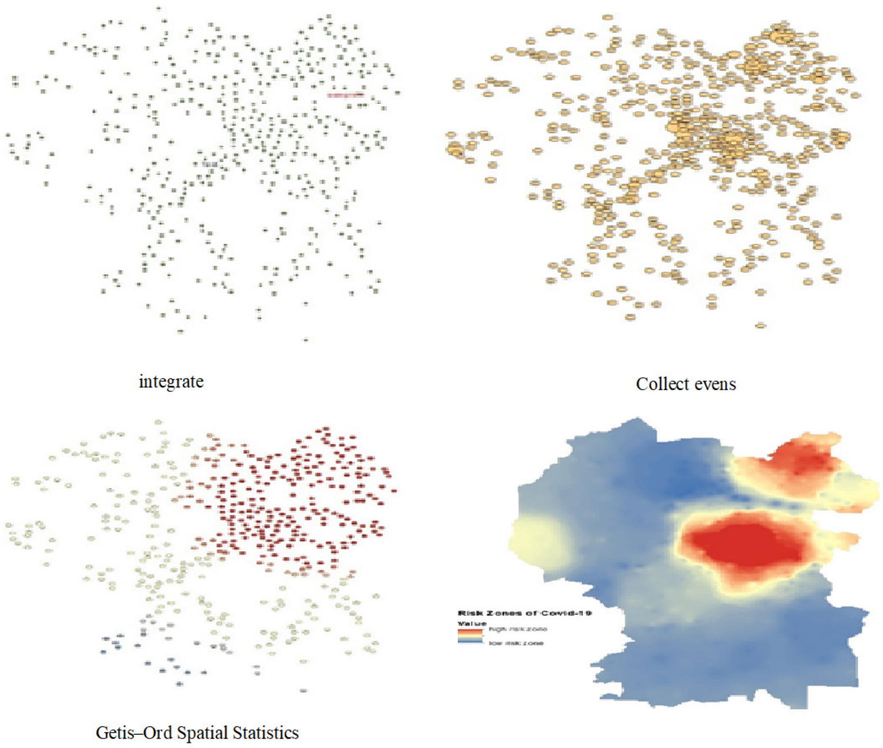


Figure 15-2: Optimized Hot Spot Analysis workflow

DISCUSSION

The results show that the three most visited venues were the shopping malls (31%) followed by the social services category which includes beauty salons, hotels, post offices, stores at 24%, and dining outlets at 21%. The least number of visits (0.8%) was to petrol stations. The result also shows the pattern of the spatial distribution of visited venues by the Kuala Lumpur public clustered at the Bukit Bintang and Wangsa Maju areas. This scenario is supported and confirmed by Moran's I and Average Nearest Neighbour analyses. The nature of the geographical distribution of points of interest in Kuala Lumpur City demonstrates that the points of interest are not randomly dispersed, but rather are concentrated. The findings also show that there is a less than 1-percent possibility that the clustered pattern is the product of random chance. The nature of the spatial distribution of POI in Kuala Lumpur City indicates that the visited venues are regularly distributed and a tendency towards clustering because it is supposed to include circles at 68.2% of the apparent elements if the distribution is regular and the result shows the ratio was at 67% which is roughly the same standard. Furthermore, an alarming 9799 cases were recorded in Kuala Lumpur City from December 1 and January 15, 2021, where Bukit Bintang districts recorded the largest number of cases with 3555 cases as compared to the lowest number of cases was in Kepong with 211 cases only. Incidentally, Bukit Bintang, Titiwangsa, and Setiawangsa districts recorded 4863 cases at a whopping 49.6%. This constituted almost half of the total cases recorded during the RMCO period. Unfortunately, the SOP of the people movement did not change during this period which caused a further escalation of cases. This indicates that the imposition of the RMCO was ineffective in curbing the spread of COVID-19. More smart approaches are therefore crucial to combat the epidemic in the future. This study attempts to contribute toward that end. The Hotspot Analysis results also suggest that the districts of Bukit Bintang, Titiwangsa, and Setiawangsa were the most frequented over the period from 1 December to 15 January 2021, according to the data collected (Figure 15). This also corresponded with the largest number of COVID-19 cases recorded in a single period (Figure 8). On the basis of these findings, it was possible to draw the conclusion that there was a significant association between patterns of people mobility and land use cover on the one hand, and growth in the number of COVID-19 instances on the other side.

CONCLUSIONS

This research used a variety of statistical approaches to uncover important mobility patterns. The findings demonstrate the suggested methodology's feasibility as a tool for extracting Spatio-temporal information. Additionally, the discovered patterns aid in the comprehension of the user's behaviours over time. POI is a valuable source of temporal information for identifying trends such as interactions between multiple locations and for tracking Spatio-temporal user interactions and locations. It is discovered that there is geographical heterogeneity in the number and relative distribution of visited locations among district residents. There seems to be an imbalance in the t movements, indicating that the people of Kuala Lumpur City are more concentrated in one region, the Bukit Bintang neighbourhood. In general, since obtaining data on human movements is difficult due to the fact that it is deemed private information, the researcher had to rely on mathematical techniques such as the Average Nearest Neighbour, the Moran I Analysis, and the Kernel density of POI as Analysis Methods. Consequently, statistics indicate that the most frequently frequented locations were retail malls, food establishments, and social services (which include stores and supermarkets). As a result, it is advocated that they be concentrated in a single location, such as a shopping complex. This minimizes the mobility of individuals and hence the number of visits. This study examined the RMCO period's efficacy using research statistics. It seems as if the pattern of human mobility in relation to land usage did not alter over this time period. That is why the number of locations visited stayed constant, but the number of COVID-19 instances increased. As a result, the RMCO regulations and terms and conditions must be examined and improved.

The availability of data is critical to any study, as it provides the required data for researchers to construct intelligent models and methods for the movement of individuals during an epidemic, therefore limiting the spread of the disease. Fundamental planning principles and standards are critical in distributing the most critical community services and facilities. As a result, the Structure Plan and Local Plans of Kuala Lumpur City must be strictly adhered to in order to prevent fragmented attractions and overcrowding in any zone. SOPs should be evaluated during the RMCO period using GIS data and simulations. Actual data on people's movement from all districts must be made open and accessible to the public.

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