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Assessing the Spatial Equality of COVID Testing Sites Maintaining Zero COVID Policy

Muhammad Sajid Mehmood[1,2,3*], Gang Li[4,5], Shiyan Zhai[1,2], Yaochen Qin[1,2], Annan Jin[4], Lan Li[4]

[1]College of Geography and Environmental Science, Henan University, Kaifeng, China
[2]Key Laboratory of Geospatial Technology for Middle and Lower Yellow River Regions, Ministry of Education, Henan University, Kaifeng, China
[3]INTI International University, Nilai, Malaysia
[4]College of Urban and Environmental Sciences, Northwest University, Xi'an, China
[5]Shaanxi Key Laboratory of Earth Surface System and Environmental Carrying Capacity, Xi'an, China
Email: *m.sajid.mehmood@hotmail.com

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Abstract

Rapid and timely testing is essential to minimize the COVID-19 spread. Decision makers and policy planners need to determine the equal distribution and accessibility of testing sites. This study mainly examines the spatial equality of COVID-19 testing sites that maintain a zero COVID policy in Guangzhou City. The study has identified the spatial disparities of COVID testing sites, characteristics of testing locations, and accessibility. The study has obtained information on COVID testing sites in Guangzhou City and population data. Point pattern analyses, Euclidian distance and allocation, and network analyses are the main methods used to achieve the research objectives, and 1183 total COVID testing sites can be recognized in Guangzhou City. Results revealed that spatial disparities could be noticed over the study area. Testing locations of Guangzhou City are highly clustered. The most significant testing sites are located in Haizhu District, which has the third largest population. The highest population density can be identified in Yuexiu District. However, only 94 testing sites are located there. According to all the results, higher disparities can be identified, and a lack of testing sites is located in the north part of the study area. Some people in the northern part have to travel more than 10 km to reach a testing site. Finally, this paper suggests increasing the number of testing sites in the north and south parts of the study area and keeping the same distribution, considering the area, total population, and population density. This kind of research will be helpful to decision-makers in making proper decisions to maintain a zero COVID policy.

Keywords

COVID-19, Testing Sites, Spatial Disparities, Spatial Equality, Guangzhou

City, Accessibility

1. Introduction

The World Health Organization declared COVID-19 a global pandemic on March 10, 2020 (Tao *et al.*, 2020), which existed for two or more years. However, it began to outbreak in the latter quarter of 2019, stroking into the global health system [1] and creating harmful economic, social, and development changes due to its fast transmission. Consequently, 95,000 deaths were recorded on May 23, 2020 [2], but it increased speedily to 6,200,571 deaths by April 19, 2022 [3]. In the same way, the number of cases recorded in a particular year was 503,131,834 [3]. However, prevention methods such as social distancing, tracing COVID-related contacts, travel restrictions, and personal protective methods like surgical masks were introduced to respond to the global issue. Inventing vaccinations, distributing them, and providing vaccination centers worldwide are influential prevention strategies [4]. However, the economic efficiency of a country with lower or higher income was founded to vaccinate gaining into a country. So, due to the changes in responding to vaccination rates, obeying lockdown policies, and mask usage efficiency, socioeconomic conditions such as death rates and infections or COVID-19-related health issues were different from region to region [5]. The National Health Commission has also declared that the fully vaccinated Chinese population calculations were 76% by November 2022. Some other Chinese have not been vaccinated because they are concerned about safety and effectiveness, and the demand for vaccinations has changed with the ongoing ideologies about the brands and their approval through WHO and other health organizations [4]. Consequently, the geography of countries has become considered a factor in control measures, such as Australia and New Zealand, which are covered and surrounded by water, has become a prominent feature [4].

The Chinese, whose results were positive for COVID-19, are isolated, and authorities implemented target movement restrictions. They should find the contacts exposed to the virus quickly while conducting PCR testing in geographical areas [4]. Further, China introduced a new strategy method called "Dynamic COVID-zero" [6], which is different from the traditional methods, considering the way of controlling the pandemic efficiency by minimizing the impacts on social, economic, productivity, day to day life of Chinese balancing the prevention and build up socioeconomic stability within a short time, under the criteria of less money expenditure, from August 2021, in responding to Delta variant, which is highly transmissible [7] [8]. The strategy helps break the transmission chain by identifying infected people by epidemic prevention staff within a day after each outbreak. It ends the process by controlling each geographical cluster quickly, preventing the outbreak of several variants like Delta, Omicron, and other variants in other regions' social and economic developments, with lower cost but higher efficiency. However, the state governments use their control strategies depending on their COVID-19 situation to prevent country-specified policies [8].

Consequently, the approach reduced the death rate in China by 25 times [9]. However, one should consider that it harms health and marginalized or vulnerable groups being socially disadvantageous [9]. The rapid source finding hidden in the population has turned with the advancement of technology in molecular biology, nucleic acid screening, and the heavier usage of extensive data analysis. For example, identifying close contacts and risk groups is implemented quickly using big data technology [8].

The international evidence relating to the mortality and morbidity of COVID-19 clearly shows some ethnic and racial inequalities. As Kim *et al.*, (2021) have implied that the testing programs have become an essential preparation to reopen the countries that were in lockdown, and country and area like South Korea and Taiwan area followed the program of organizing to facilitate networks of drive-through testing by tracing contacts, but then take the case of the United States, standard federal level testing has not been available due to establishment difficulties for governments effectively [10]. Consequently, South Korea could meet its testing rate 5200 per million individuals. The United States could only achieve a testing rate of more than 74 per million individuals by the middle of March 2020. Further, it implies minorities in racial or ethnic are doing the majority of essential working jobs by having low wages during the pandemic, which increases the risk of exposure to COVID-related contacts. That may be the reason why the number of hospitalized and mortality of non-Hispanic Blacks, Hispanics, American Indians, and Alaska Natives are relatively higher than non-Hispanic whites in the United States [11] [12].

On the other hand, minority communities have been faced with some difficulties in accessing testing sites in many parts which have addressed racial or ethnic disparities in the United States. Notably, 70% of the first hundred COVID-related deaths in Chicago were African Americans [10]. However, ethnic or rational-based infections and deaths have changed over time due to rapid transmission [13]. However, according to Kim *et al.*, (2021), Lanix or black holds are crowded in the United States relative to Whites and suspected majority cluster who may have been exposed to contacts, living in populated families has to face difficulties maintaining social distancing at home to keep the safety of family members [10]. Moreover, the personal income rate inequalities also have become a factor for responding to accessing healthcare services, engaging in prevention programs, and determining the exposure of inequities in risk in most countries, having a direct consequence on the physical health and mental health of lower-income generated people comparing to the higher income population [5]. On the other hand, rural counties with a majority of Black or Indigenous residents had higher rates of premature death, food insecurity, and unemployment, as well as lower median incomes before COVID-19, while comparing the rural areas with suburban and urban areas, rural areas in Florida, have older populations and higher rates of underlying health conditions, making older adults and rural communities particularly vulnerable to COVID-19 [1]. Overall, the Black American population in West Virginia lives in urban areas, where the foods are more secure and have been prioritized in positivity testing for COVID-19 [14]. COVID-19-related social disparities are based on testing inequality arising with the color of communities' living conditions, whether rural or urban—further, food insecurity and economic poverty [14]. What is more, strict lockdowns created tremendous impacts on health problems like chronic kidney and heart diseases, stroke, and cancer patients, which should maintain a checkup routine and re-examine treatments due to limited treatment resources. Take the case of the omicron wave in Shanghai; the patients whose PCR (polymerase chain reaction) was positive were not allowed admission to hospitals due to strict COVID-related policies. However, the authorities have provided online methods for specialist consultations, registration and bookings, home drug deliveries, and medical insurance payments to overcome the problems [7]. However, early studies on the COVID-19 pandemic assessed accessibility to testing locations using quick actions by taking testing capacity, population demands, and travel distances into consideration than the figure out social inequality-related cases recorded in the environment of Corona outbreak in worldwide [13].

Although the Chinese government has already changed the policy to take and manage COVID-19 as the "Class B" virus, visualizing the geographic distribution patterns of COVID-19 testing sites is essential to understand the testing access for the vulnerable population, and this paper mainly examines the geographical disparities of COVID-19 testing sites in China. The aim of this study is to [1] assess the spatial pattern of testing site distribution in the study area, [2] characteristics of the testing sites, and [3] spatial accessibility, equality, and inequality location matters for zero COVID policy. This study shows the disparities in accessibility to testing COVID-19 and guides future efforts to allocate testing sites equitably.

2. Study Area and Data

2.1. Study Area

This study was conducted in Guangzhou, China. Guangzhou is one of China's five national central cities, the capital of Guangdong Province, and the main hub of the Pearl River Delta [15]. It was built 2228 years ago and was the first city in China to establish trade relations with the outside world, known as China's "southern gateway" [15] [16]. Guangzhou is a modern city in China, serving as the political, economic, educational, cultural, and technological center of Guangdong Province and southern China [15]. The city covers an area of 7434 square kilometers and has a population of over 20 million with 10 million short-term residents [15]. Guangzhou is highly urbanized. The proportion of the urban population has continued to grow over the past seven years, exceeding 80%, far above the national average [16]. The location map of Guangzhou is shown in **Figure 1**.

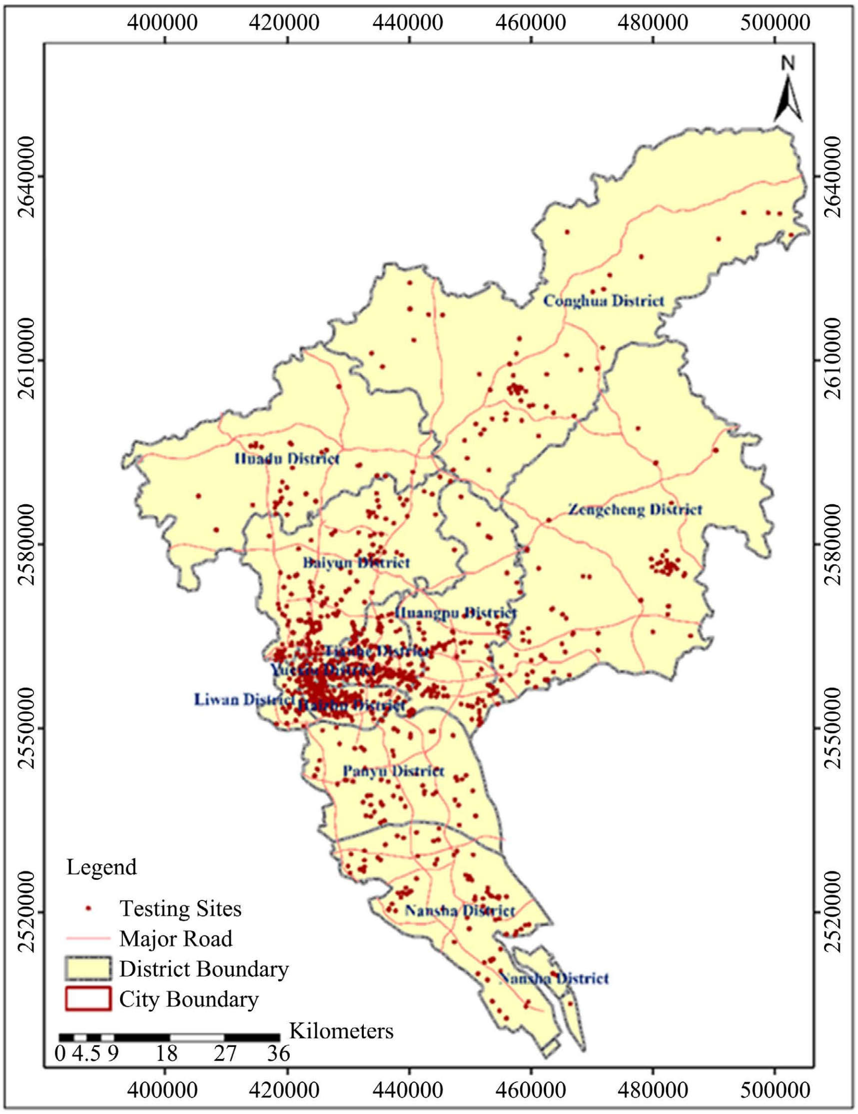


Figure 1. Study area map of Guangzhou, edited by the authors, source from https://nr.gd.gov.cn/map/bzdt.

Guangzhou is China's third largest medical center, with 5093 medical facilities (including 269 hospitals) and 6.5 beds per 1000 people. Health services are available in 15 minutes in urban and 30 minutes in rural areas. Eight national or regional medical centers in Guangzhou, including the First Affiliated Hospital of Guangzhou Medical University, are registered as the National Respiratory Medicine Center. The top 9 national hospitals in Guangdong are located in Guangzhou, among which 5 are specialized hospitals for treating COVID-19 patients.

Guangzhou is an international transportation hub with 15.3 million residents in southern China. On January 21, 2020, Guangzhou reported its first COVID-19 imported case. A total of 557 cases of COVID-19 symptoms were reported from January 21 to June 30, 2020. Since May 2, 2020, no local cases have been reported for more than 5 months. Guangzhou is one of the cities that experienced the early, mid-term, and recovery stages of the COVID-19 outbreak [17].

2.2. Data

The study has used COVID-19 testing sites located in Guangzhou City and sites' locations and the information obtained from open Application Programming Interface (API) (platform of Gaode Maps (https://www.amap.com/), which is one of the most extensive Web mapping, navigation, and Location-based services (LBS) platforms in China [18]. Population data for 11 districts of Guangzhou City were collected from the Guangzhou Statistics Bureau [19].

3. Methods

3.1. Point Pattern Analysis

Point pattern analysis using ArcGIS was calculated to examine the spatial dynamics of COVID-19 testing sites in Guangzhou City. Assessing spatial dynamics is essential for understanding how testing sites are varied. Both density-based and distance-based approaches were applied in this paper as follows;

3.1.1. Kernel Density

Density-based approaches characterize the distribution pattern of points, and this paper used Kernel density to identify the spatial dynamics of COVID-19 testing sites in Guangzhou City. The kernel density method is an extension of the square method: like the square density, the kernel method calculates the local density of a subset of the study area, but its corresponding terms for the square density are different, with overlapping sub-regions providing movable subsets. The kernel density method generates a density grid with pixel sizes smaller than the kernel window. Assign the calculated density value of the Kernel window centered on each pixel. Equation (1) describes the Kernel Density estimation.

$$\lambda(s) = \sum_{i=1}^{n} \frac{1}{\pi r^2} k\left(\frac{d_{is}}{r}\right) \tag{1}$$

where $\lambda(s)$ is the density at location s, r is the search radius of the Kenel Density Estimation, k is the weight of a point i at distance d_{is} to location s. k is usually modeled as a function of the ratio between d_{is} and r. As a result, rather than choosing a uniform function that gives equal weight to all points within the radius r [20].

3.1.2. Average Nearest Neighbor Analysis (ANNA)

The spread or distribution of something over a geographic area is measured via nearest-neighbor analysis. It offers a number that expresses how closely together or evenly spaced a group of points is. ANNA assesses the average distance between each point in the Guangzhou area and its nearest point. This paper calculated the nearest neighbor index based on the average distance between each COVID-19 testing site and its nearest neighbor site. The average distance from the nearest neighbor measures the rarity of points in the distribution.

The average nearest-neighbor ratio is determined as the difference between the observed and expected average distances, where the expected average distance is based on a fictitious random distribution with the same number of features covering the same total area [21]. ANNA can calculate using the Equation (2).

$$\text{ANNA} = \bar{D}_O / \bar{D}_E \tag{2}$$

where $\bar{D}_O$ is the observed mean distance between each feature and its nearest neighbor and $\bar{D}_E$ is the expected mean distance for the features given in a random pattern.

3.2. Text Mining

This paper used the word cloud plots to examine the characteristics of COVID-19 testing sites in Guangzhou City. A word cloud is a picture that visually displays word data. In other words, it is a group, or cluster, of words shown in various sizes. The more often and how essential a word is stated in a document, the larger and bolder it appears. Due to its ability to quickly reveal the most important or popular topics, word cloud visualization is particularly popular among presenters. Word clouds can be used as a summary, providing instant analysis & visualization of word data and feedback and providing insight into the most popular concepts or convey sentiment [22]. This paper used R's word cloud package and the Rcolor Brewer package for colors. Additionally, the wordcloud2 package in R, which has a slightly different appearance and entertaining uses, can also be used to produce word clouds. This method has been used to investigate the attribute data described in the testing locations in Guangzhou City. It has imaged the keywords found in the attribute, and the size depicts the frequency of the word.

3.3. Spatial Accessibility

A network is a collection of interconnected components, such as edges (lines) and junctions (points), that show potential paths between two points. Utility networks and network datasets are the two types of networks that fall under the ArcGIS software. The ArcGIS Network Analyst extension to create and edit network datasets. Network analysis can be used to identify the quickest way to get from one selected location to another location [23]. This paper mainly used a location-allocation tool to assess the testing facilities from each centroid and assess the new location requirement to locate testing sites in each district with the demand.

3.4. Euclidean Distance

Mathematically, the length of a line segment connecting any two points in Euclidean space is known as the Euclidean distance between them. The minimum distance between two pairs of points from the two objects is typically used to determine the distance between two objects that do not point. The distance between two points is known as the Euclidean distance in coordinate geometry. The length of the line segment separating the two places should be measured to determine the distance between them [24]. Euclidean distance can be calculated using Equation (3). Where "d" is the Euclidean distance, (x_1, y_1) is the coordinate of the first point, and (x_2, y_2) is the coordinate of the second point.

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{3}$$

3.5. Euclidean Allocation

Euclidean allocation produces a grid where each empty cell is assigned to the source nearest to it. The nearest source is determined by Euclidean distance. Sources are all of the cells with a value, including zero. Empty cells are cells with no value. The value of the nearest target cell from the input picture, as determined by the Euclidean distance (*i.e.*, straight-line distance), is assigned to grid cells in the output image using this tool [25]. This paper has used this to understand each testing site's service area and estimate the areas for new testing locations in the study area.

3.6. Density Maps

Density mapping demonstrates where points or lines could be clustered in a specific region. These maps frequently use interpolation techniques to predict where a particular feature's concentration (for example, population) could be throughout a given surface. Point density, line density, kernel density, and choropleth maps are examples of different density maps [26]. This study calculated the population density to understand the area with a higher population in Guangzhou City. Population density is the number of people in a given area of land. It primarily applies to people, yet it occasionally does to other living things. It is a crucial geographic phrase. The number of people living in an area per square kilometer, or another unit of land area, is called population density. Population density can be calculated using the following equation.

$$\text{Population density} = \text{number of people} \div \text{the area they occupy} \tag{4}$$

The density map is presented using choropleth maps, and a choropleth map is a kind of statistical thematic map that uses color that correspond to an overall summary of a geographic characteristic within spatial enumeration units, such as population density. A simple way to see how a variable varies geographically or the degree of variability within a region is to use choropleth maps. The flow chart of the paper methodology is shown in **Figure 2**.

4. Results

4.1. Spatial Disparities and Characteristics of COVID-19 Testing Sites in the Guangzhou City

The spatial distribution of COVID-19 testing sites and population density in Guangzhou City is shown in **Figure 3(a)**. There are 1183 total testing sites, and the results indicated that spatial disparities could be noticed. The highest testing sites are in Haizhu District, located in the city area with a 1,819,037 total population. The higher population in the Haizhu District lives in an area of 92.04

sq·km. The population density of the Haizhu District is 19,763, and it is the third highest in Guangzhou City. The number of testing sites and population density of each district are shown in **Table 1**. The highest population density (30,841) can be recognized in Yuexiu District, and the second highest is in Liwan District. There are 94 and 55 total testing sites, respectively. The lowest testing sites, 43, are located in the Huadu District, with a population density of 1699. Results revealed in this study have shown that testing facilities are not equally distributed throughout the study area.

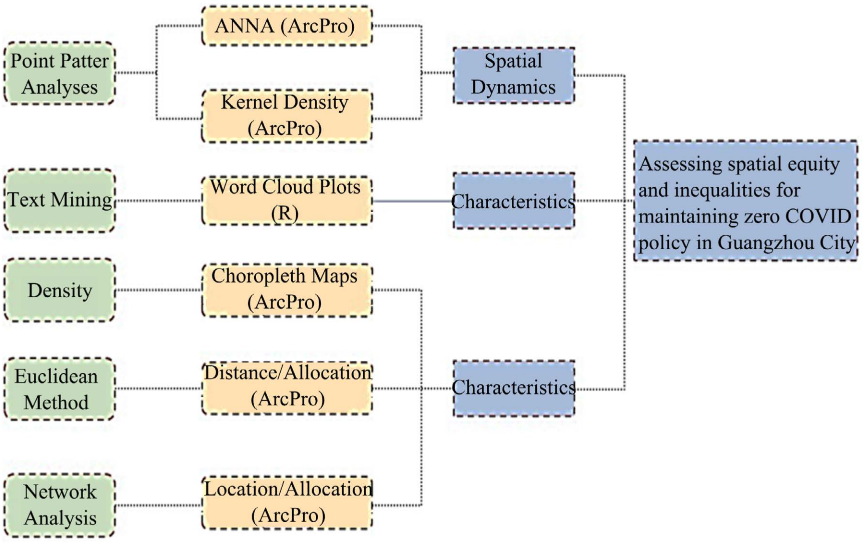
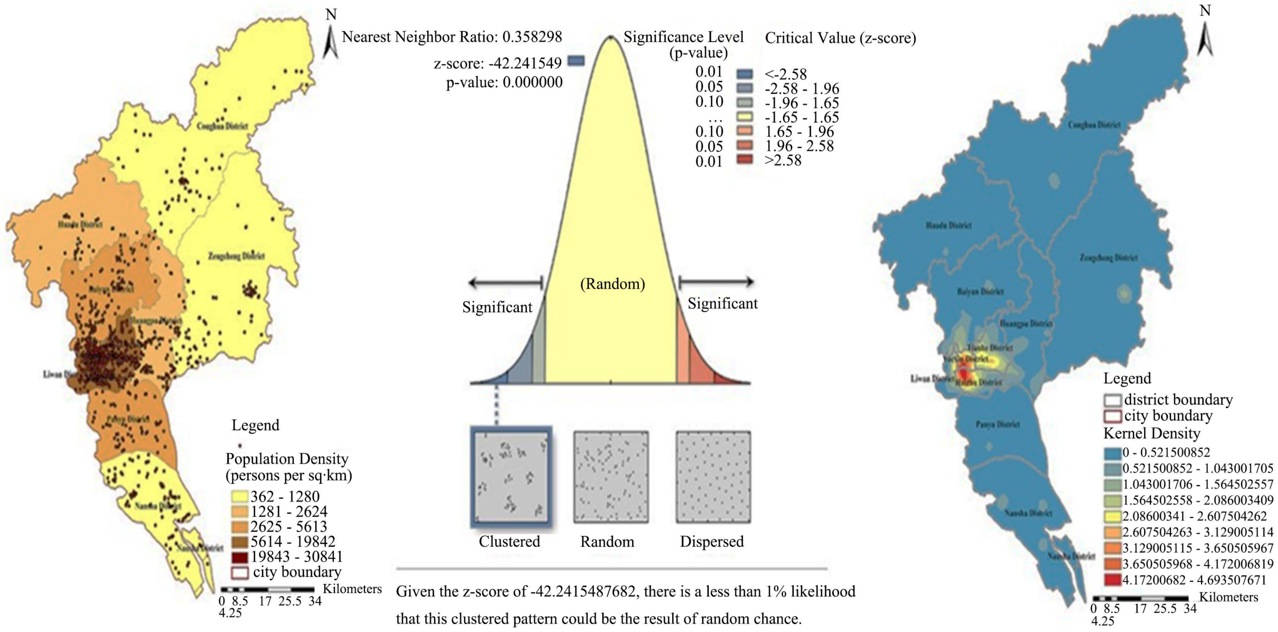


Figure 2. The flow of the methodology.



(a) (b) (c)

Figure 3. Spatial disparities of COVID testing sites in Guangzhou City. (a) Population density per square kilometers, (b) Results of the ANNA, (c) Kernel density map of Guangzhou province. Edited by the authors, source from https://nr.gd.gov.cn/map/bzdt.

Table 1. Total number of testing sites and population density by districts.

District Name	Area	Population	Population Density	Number of Testing Sites	Testing sites owned per capita
Conghua	1984.94	717,684	362	65	0.180
Nansha	661.17	846,584	1280	106	0.083
Yuexiu	33.67	1,038,643	30,841	94	0.003
Liwan	62.4	1,238,305	19,842	55	0.003
Huangpu	481.82	1,264,447	2624	126	0.048
Zengcheng	1614.05	1,466,331	908	89	0.098
Huadu	966.64	1,642,360	1699	43	0.025
Haizhu	92.04	1,819,037	19,763	173	0.009
Tianhe	136.17	2,241,826	16,463	187	0.011
Panyu	516.03	2,658,397	5152	74	0.014
Baiyun	666.81	3,742,991	5613	171	0.030

In addition, inner cities of the Guangzhou Province, Yuexiu, Liwan, Tianhe, and Haizhu, have shown the highest aggregation of the COVID testing sites. The outer part of the inner cities (suburbs), mainly Luogang, Baiyun, Huangpu, and Panyu, have recorded fewer testing sites. However, some cluster areas can be recognized in the suburbs of Guangzhou. Outer city areas (primarily rural): Conghua, Huadu, Zengcheng, and Nansha have the lowest-density population and the lowest number of testing cities. Moreover, two prominent clusters can be recognized in the Conghua and Zengchend areas. Therefore, significant urban-rural disparities can be observed with the spatial distribution of COVID testing sites in the province, and testing sites have also been distributed according to the population density of the study area. The inner and outer suburbs have many COVID testing sites, and the outer part of the province has fewer health facilities than the Guangzhou Province.

The result of the ANNA is shown in **Figure 3(b)**. According to **Figure 3(b)**, testing locations are highly clustered. The nearest neighbor ratio is 0.36. Testing sites in Guangzhou City are concentrated in the city area, and the highest density can be recognized (**Figure 3(c)**). It has gradually decreased from the city area to the outer part of the city. Some higher-density clusters are located in every district in Guangzhou city. As the above results described, there are higher disparities in testing sites' spatial allocation in Guangzhou City.

This paper presents characteristics of testing sites using word cloud plots in **Figure 4**. As shown in **Figure 3**, testing sites are mainly distributed around the urban areas. Guangzhou and Guangdong are the significant areas with the highest testing sites. They have focused on locating very close to the roads and cities. Guandong has repeated 936 times, and most sites are distributed in the city areas. Testing sites are in green areas, villages, parks, and riversides. However, there are few testing sites in these areas.

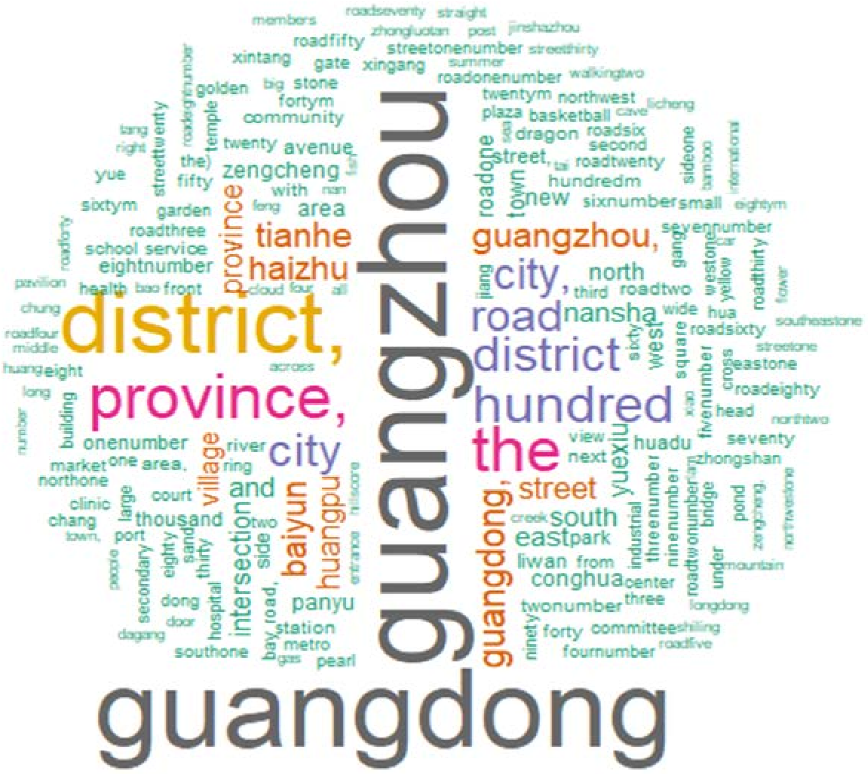
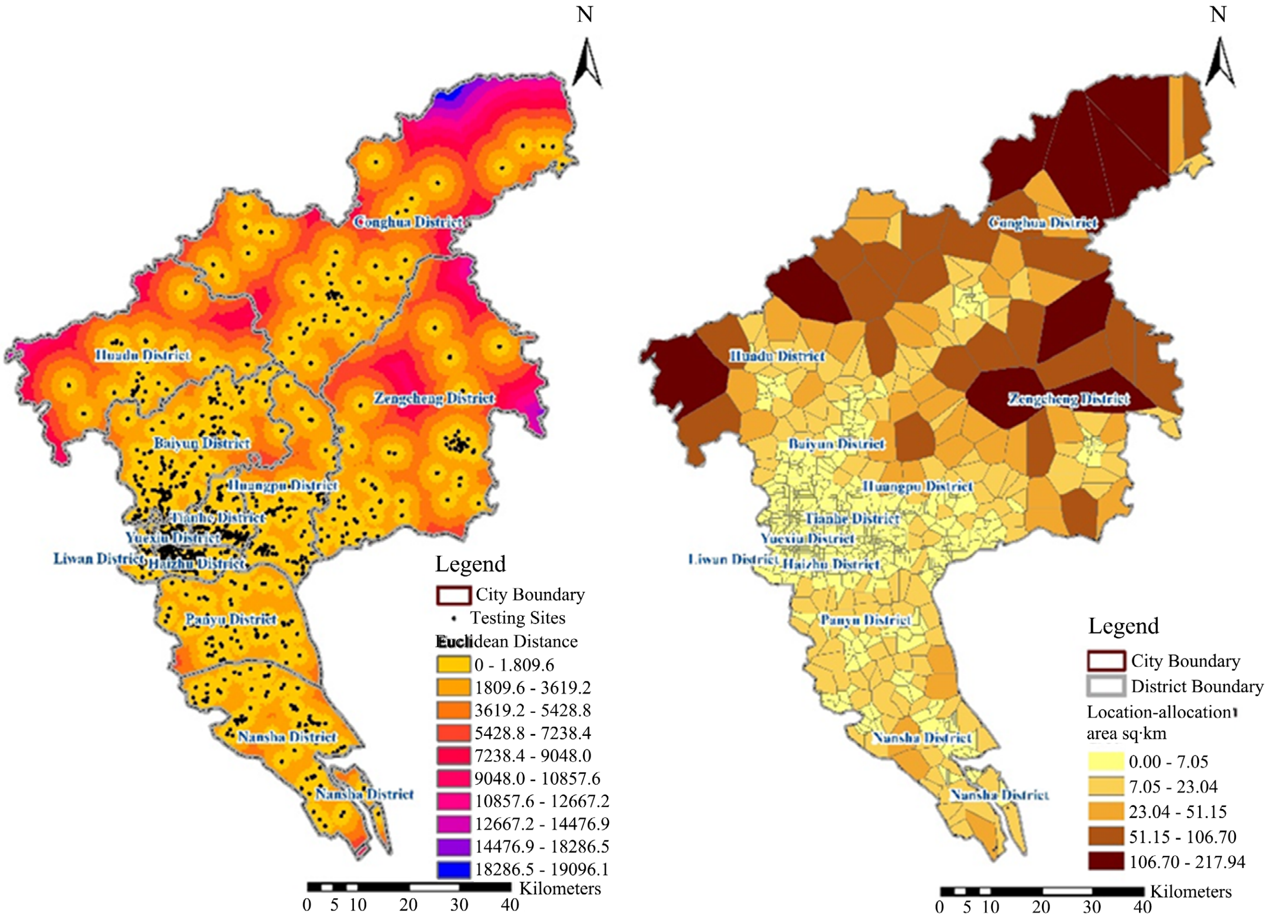


Figure 4. Word cloud plot for describing the testing locations.

Hospitals and health care centers are the primary testing locations in Guangzhou, and health has been repeated 1174 times. Hospitals have shown 174 repeated times in the word cloud plots in the study area. Schools, stations, and university locations are included but not prominent. Conghua District, Zengcheng District, and Huadu District have shown lower population density than the other districts in Guangzhou City, 362 sq·km, 908 sq·km, and 1699 sq·km, respectively. Nansha District has a low-density population (1280 sq·km) compared to other districts. However, it consists of 106 testing sites around the city. Liwan has a 19,842 population density, and only 55 testing sites can be recognized. Baiyun District has the highest population of 3,742,991 and 171 testing sites. These testing sites are not distributed equally throughout the district. The second highest population density (2,658,397) is in Panyu District, and only 74 testing sites are located there.

4.2. Spatial Accessibility, Equality, and Inequality's Location Matters for Zero COVID Policy

Euclidean distance, allocation, and location-allocation methods are used to assess the accessibility, equality, and inequalities of testing site distribution in Guangzhou city. The Euclidean distance and allocation are shown in Figure 5(a) and Figure 5(b). Good accessibility and equal facilities are distributed in the study area's higher urban and southern parts. Figure 5(a) shows that the lowest distance between locations can be recognized in the Baiyun District, Tianhe District, Yuexin District, Liwan District, and Haizhu District. Testing site locations in the south part are also shown a similar pattern. However, the maximum distance between the points is nearly 10 km, and a higher distance can be recognized at the edge of the study area in the southern part.



(a) (b)

Figure 5. (a) Euclidean distance, (b) Euclidean allocation. Edited by the authors, source from https://nr.gd.gov.cn/map/bzdt.

Moreover, the north part of the study area presented a different pattern, and the highest distance of 18 km was recorded. Most of the testing sites in the North Part have been distributed monotonously along the main roads. However, some major town areas show a clustered pattern of testing site distribution. According to these results, the testing sites are not distributed equally throughout the study area.

The Euclidean allocation has shown the estimation of a service area for each testing location in the study area. Small service areas can be depicted in the urban cities in the study area, and it is less than 1 sq·km from the testing site. However, this pattern is unequal throughout the study area, and the highest service area can be recognized, Conghua District, in the northern part of the study area. The highest service area is more than 200 sq·km. Service areas with >100 sq·km are located in Conghua, Huadu, and Zengcheng Districts in Guangzhou City. Furthermore, the upper part of the study area is also shown as a small service area with less than one sq·km along the main roads, and other village areas have not shown good accessibility for the COVID-19 testing sites. Almost 21 testing sites have shown 50 to 100 sq·km as their service area.

Figure 6 shows the distance from the districts' centroids to each testing site in Guangzhou City. There are 255 testing sites away from the city, and >ten sq·km distance can be shown. Around 30 locations are very close to the center locations, and 809 locations have shown a 1 - 10 sq·km distance from the city centers. Very few testing centers are located in rural areas, and there is no high relative accessibility. The largest districts, namely Conghua District, Zengcheng District, and Huadu District, lack testing services. Testing sites are located on every side of the centers of Baiyuan District, Tianhe District, Yuexin District, Haizhu District, and Liwan District. However, other districts have not covered all the areas, and testing sites are insufficient to cover the whole area with reasonable accessibility. Sometimes, people must travel more than 10 km for a testing site in these districts. However, the testing location distribution of Panyu District is better than other districts. Inequalities in the spatial distribution and accessibility of testing sites can be identified.

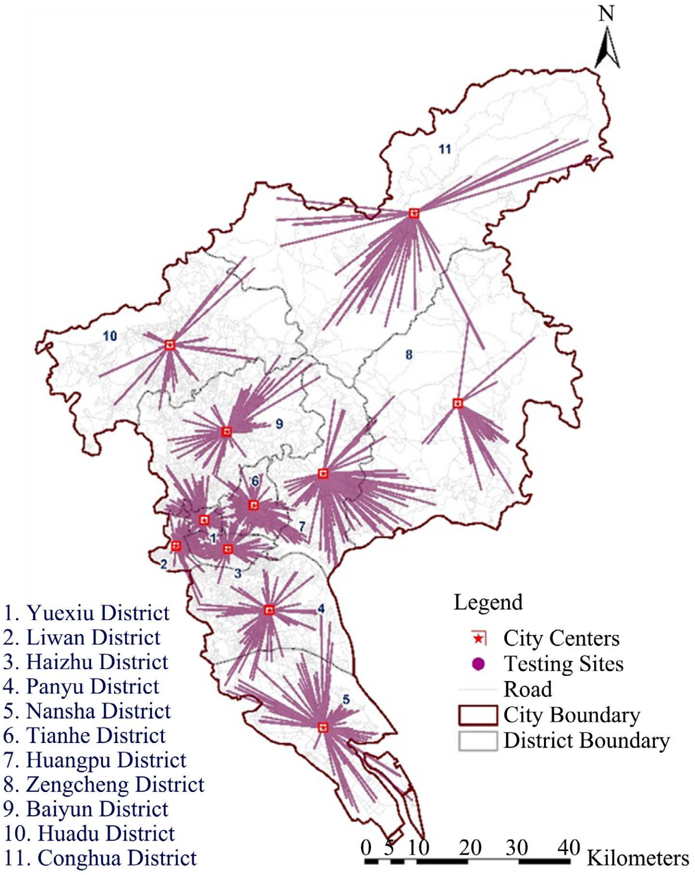


Figure 6. Distance lines from the centroids of the districts to each testing site. Edited by the authors, source from https://nr.gd.gov.cn/map/bzdt.

Mainly, the inner suburbs of the Guangzhou Province have shown reasonable proximity and accessibility to COVID testing sites, which is significant for good accessibility. The people of this area can be reached at the testing sites traveling a short distance, and all sites are located within a minimum of 1 km area. Most of them have equal accessibility. However, this situation is recorded differently in the study area's outer or rural part, and low accessibility can be recognized.

5. Discussion

Guangzhou is China's central city, consisting of 11 districts. This study was conducted in Guangzhou City to examine the spatial dynamics and accessibility of COVID-19 testing sites. As our significant findings described, equal distribution of testing sites is essential to providing better service to people. First, as the results of this paper reveal, the highest population is in the Baiyun District, and the population density is 5613 per sq·km. The total number of testing sites located in this district is 171. The lowest population is 717,684 in Conghua District, and the population density is 362 per sq·km. The total number of testing sites is 65. However, some districts with higher population and population density show fewer testing sites in Guangzhou City. For instance, Yuexiu has the highest population density (30,841) district, and its population is 1,038,643. However, the total number of testing sites is 94. Liwan is the second-highest population density district, and 55 testing sites are located. Huadu population is 1,642,360, and the population density is 1699. This district has shown the lowest number of testing sites in Guangzhou City. These results have clearly shown the inequality distribution of testing sites, and testing sites should be located considering the area, population, and population density in an area. Therefore, it is necessary to establish other new sites for Conghua District, Huadu District, and Zengoheng District in Guangzhou City. A comprehensive understanding of the inequality distribution of testing sites and the significance of considering area, population, and population density in site location decisions can be achieved. These studies collectively underscore the importance of addressing disparities in testing site distribution to ensure fair access to testing services for all populations [27]-[30].

The study has shown that the Haizhu District and Tianhe District have more testing sites, and most of the urban areas in Guangzhou City have excellent testing sites and accessibility. Most testing sites are concentrated in urban cities. Therefore, spatial cluster distribution can be identified throughout the study area. Some people can easily access testing services and health care with these clusters, while others cannot. Therefore, equal distribution is essential for equal services. Understanding the spatial distribution of testing sites and healthcare services is crucial for addressing disparities and ensuring equal access to care for all individuals, regardless of their location [31] [32]

Third, many disparities can be recognized away from the urban cities, and the Northern part of the study area shows the linear distribution of COVID testing sites. Most testing sites are located along the main roads, and people living away from the main roads must travel more time to reach the testing facilities. The accessibility is lower than in urban cities. The disparities in COVID-19 testing site distribution between urban and rural areas have been a significant concern. Rural areas often face challenges with accessibility to testing facilities, with fewer sites available compared to urban areas [33]. The word cloud plots show that urban-related words are the most repeated words. The village, green areas, and parks are shallow, and rural areas can be shown to need testing sites. Therefore, moving some testing locations to the rural or outer part of the urban cities in Guangzhou City is very important.

Unequal distribution of COVID testing sites can mainly recognized in the area. However, the inner part of the study area can be recognized as having equal distribution and good accessibility to testing sites. These inequalities have been recorded from the beginning of the study area's COVID-19 pandemic. Most rural people have become vulnerable to COVID-19 with the low facilities and accessibility to testing centers [34].

In addition, the results of the network analysis also show these disparities. Testing sites are located throughout the urban areas but differ in other areas. Especially the northern part of the study area. Some people have to travel nearly 20 km to reach a testing site for their health care. Most people must travel 10 - 15 km to find a testing location. Due to this situation, it is necessary to establish more sites in the northern part of Guangzhou City. Finally, this study can be suggested to decision-makers and policymakers to establish healthcare sites, considering the population, population density, area, and accessibility. By considering these things, people can get their facilities very quickly [35].

The city has faced many difficulties regarding increasing or promoting equality of testing site locations, and vulnerable people should be focused on establishing testing sites in the area. Socioeconomic background also needs to be considered when establishing testing sites, and it should be given more priority to aging people. They cannot travel more distance to reach the centers. Therefore, age and poverty need to be considered. With the low income of the outer part of the province, people do not have good accessibility to travel, and their paradigm should also cause these issues.

6. Conclusion

This paper mainly examines the spatial disparities of COVID-19 testing sites in Guangzhou City. The paper has mainly discussed the spatial disparities of testing locations and their characteristics and accessibility. The paper has used both statistical and spatial analyses to achieve the main objectives of the research. Point pattern analyses, network analysis, Euclidian distance analysis, and density calculations are used as research methods. The study's results mainly revealed that Tianhe District has the highest number of testing sites (187). The highest population is in Baiyun District, and 174 testing sites are located there. As results have shown, the testing sites have not been established equally over the study area, and most of them are consecrated to the urban cities, and people can reach the testing sites quickly by traveling less than 1 km distance. However, some people in rural or outer parts of the city must travel more than 10 km to reach their testing site and get health care. The healthcare service areas are much more significant in the northern part of the city, and urban and man-road areas show fewer service areas for each testing site. Therefore, this study can be suggested to establish a new testing location in the northern part of the city, and this study will be helpful for decision-makers and policymakers in establishing a COVID-zero city. The government should also focus on the socioeconomic disparities in Guangzhou Province to establish future health centers to minimize the vulnerability of different pandemics.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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