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Examining Spatial Relationship Between COVID-19 Pandemic and Population Density: Muscat, Oman, A Case Study

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Abstract

In the second half of November 2019, the Chinese government officially confirmed the detection of the first case of COVID-19 in Wuhan city. Subsequently, the pandemic began to spread dramatically across the world. By March 2022, the World Health Organization (WHO) announced the COVID-19 transmission as a pandemic. The organization recommended world governments to start the lock down procedures. These procedures affected many economies across the globe. The initial impacts focused on the public sector, particularly the public transportation and tourism sectors. Social life was also affected, and work behaviours switched to being online. According to WHO, by mid-January 2022, the number of registered COVID-19 cases reached 346 million infections, and 5.5 million deaths were associated with the pandemic. A large number of scientists from diverse backgrounds and specializations, sought to study this phenomenon and to determine the factors that led to its trending growth and spreading. Geographical features, both natural and human, played a role in this surge. Therefore, this research aims to verify the possible links between population density and epidemic transmission. According to previous studies, this topic is still debatable among scientists. Therefore, this research used two types of density: general density and physiological density combined with GIS tools and statistical analysis to confirm the relations. The results of Parson's coefficient analysis indicate a clear positive correlation reaching 0.76 when using physiological density. On the other hand, when using general density, the relationship was weak and reached 0.4.

Keywords: *COVID-19, Population Density, Muscat, GIS.*

Introduction

From the deaths of civilians to the crashing of economies, the COVID-19 transmission has had a destructive impact on all of humanity. In December 2019, the Chain government officially confirmed the first case of COVID-19 which was discovered in Wuhan city (Gallina & Ricci, 2020; Al-Kindi et al. 2021; Mansour et al., 2021; Nazia et al., 2022; Kianfar et al., 2022). The virus then transmitted rapidly through neighbouring countries. The World Health Organization (WHO) on January 29, 2020, confirmed the COVID-19 became an epidemic (Al-Kindi et al. 2021; Mansour et al., 2021; Nazia et al., 2022; Kianfar et al., 2022). After one and half months, WHO announced again that the virus became a global pandemic. The main symptoms of COVID-19 are cough, sputum production, shortness of breath, and fever; another musculoskeletal symptom cluster includes pain in the muscles and joints, headaches, and fatigue; and a third digestive symptom cluster, which includes nausea, vomiting, and diarrhea (Ali Mohamadi et al., 2020; Tavakoli Fard et al., 2022). By January 23, 2022, over 346 million cases and more than 5.5 million deaths have been reported in a total of213 countries (WHO, 2022). Until now the origin of COVID-19 remains a subject of discussion and research, however, most scientific researchers agreed that the virus is spread by close contact with infected people and their contaminated property (Guo et al., 2020; Peeling et al., 2020; Mishra et al., 2020; Arif and Mahmood, 2023). The COVID-19 pandemic has had a massive global impact on physical and human environments (Al-Kindi et al., 2021) threatening the life of people world-wide. During this pandemic several scientists and scientific research centres have tried understanding the relationship between the spread of COVID-19 and any relation with environmental, demographic, and socioeconomic issues (Ahasan et al., 2020; Bagal et al., 2020; Mollalo et al., 2020; Pourghasemi et al., 2020; Al-Kindi et al., 2020; Al-Kindi et al., 2021; Mansour et al., 2021; Pramanik et al., 2022; Nazia et al., 2022; Santos et al., 2024). Therefore, WHO and national health service authorities around the world responded quickly to slow down the spread of the COVID-19 virus by recommending several strategies such as social

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and physical separation, wearing masks and gloves, and washing hands (Khachfe et al., 2020; Arif and Mahmood, 2023).

As the level of globalization, urbanization and environmental changes increase, infectious outbreaks such as COVID-19 epidemics have become global threats that require collective actions between governments and international authorizations (Pak et al., 2022). The COVID-19 pandemic has adversely affected human health and millions of people's deaths worldwide (Mishra et al., 2020), leading to major disruptions in the world economy and the closing of many commercial industries and educational institutions. The nature of completing work has also changed, for example, governments and business services have been enforced to be completed online. Tourism sector has been completely affected and shutdown. The COVID-19 pandemic also caused a social and economic crisis, such as the increase of unemployment, which directly affected people's average income (Harapan et al., 2020; Pak et al., 2022). The virus spreads mainly through respiratory drops produced by conversations or coughs landing on surfaces or objects touched by other people, resulting in the transmission of the virus. Therefore, reducing people's close contact and increasing regular surface disinfection has become an important strategy in combating the epidemic.

Geographical information systems (GIS) have a long history associated with health services (Noble et al., 2012; Lovett et al., 2014; Ahasan, R., & Hossain, 2021; Franch-Pardo et al., 2021, Nazia et al., 2022; Al-Awadhi et al., 2022). It is a crucial tool used to analyze the spatial distribution of any natural and human phenomena including infectious diseases (Mollalo et al., 2019, 2020). It is also able to evaluate health services provided to the residents equally and effectively. This positive efficiency of a well examined health service will help control infectious diseases, especially during epidemics (Lovett et al., 2014; Mollalo et al., 2020). During the crisis, GIS has become a substantial approach to study COVID-19 transmissions. Johns Hopkins University, for example, used GIS tools to produce a dashboard that provides a live spatial data of COVID-19. From this dashboard, users can extract live information about the number of confirmed COVID-19 cases, like the recoveries and deaths of any country (JHU CSSE, 2020; Mollalo et al., 2020). Throughout the pandemic, a large number of scientific papers were published using GIS or related technologies. Several review papers highlighted different GIS methodologies and techniques to manipulate and analyze COVID-19 transmission (Franch-Pardo et al., 2021; Nazia et al., 2022). They found most of these studies focused on: local Moran's I, Hotspots and clustering, Spatial regressions, Kernel density, Interpolation techniques and geostatistics. Kamel Boulos and Geraghty (2020) also reviewed several online dashboards using GIS technologies such as the WHO dashboard, HealthMap, utilizing GIS mapping to determine health care priority during COVID-19 pandemic (Lakhani, 2020; Gibson and Rush, 2020).

Mollalo et al., (2020) used GIS-based spatial modelling to identify the number of COVID-19 incidence rates in each state in United States. The study also showed the income inequality was the main influential reasons in explaining COVID-19 rate distribution in the USA. GIS techniques were also used to monitor spatial distribution of the COVID-19 pandemic in Afghanistan by Inverse distance weighted (IDW) interpolation and hotspot analysis (Haider et al., 2022). The same methods were implemented in Qatar to identify electricity consumption. Hot/coldspots and IDW techniques were used to weigh electricity consumption during and after the pandemic in sex different landuse (Flats, Villas, Hotels, Governments, Commercial and Industrial) classes (Al-Awadhi et al., 2022). GIS techniques were also used to identify cumulative incidence rate (CIR) of COVID-19 worldwide by using spatiotemporal analysis and hotspots detection (Shariati et al., 2020). The study concluded that the pandemic was concentrated in Europe, while Africa was less affected. In addition, the spatiotemporal analysis approach was used to understand the spatial distribution of the COVID-19 pandemic in six Chinese cities (Lan et al., 2024) and in India to trace the spread of COVID-19 (Gupta et al., 2020 & 2024). Kianfar et al., (2022) applied spatiotemporal modelling by using artificial neural network (ANN) algorithm to monitor the prevalence of COVID-19 and mortality at a global scale.

By tracing previous studies, several GIS models were used to study the pandemic of Corona. These models can be divided into several groups depending on methodology, application, and tools. Franch-Pardo et al., (2020 and 2021) summarised five GIS applications for COVID-19 including Spatial statistics, Multicriteria analysis, Remote sensing and unmanned aerial vehicles, GPS and networks, and Web maps. Some of these

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studies agreed that the movement of infected individuals to places with dense population concentrations is the reason for the acceleration of the transmission of COVID-19 (Adam et al., 2020; Chang et al., 2021; Yang et al., 2024). Other research studies conducted in recent years have shown that the impact of the pandemic in cities is not homogeneous (Biswas, 2020; Kihato & Landau, 2020; Sciuva, 2024). In addition, many studies have focused on density, the main factor contributing to the COVID-19 outbreak (Boterman, 2020; Hamidi et al., 2020; Lin et al., 2020; Sciuva, 2024). However, other studies showed that the results are unclear (Sharifi and Khavarian-Garmsir, 2020) and there are still uncertainties about the actual relationship between high population density and the increased spread of COVID-19. Sciuva (2024) tried to understand the role of population density, in relation to the spread of the pandemic through the exploration of this relation in four cities: London, New York, Roma and Sao Paulo.

There are several research studies about COVID-19 in Oman (Kindi et al., 2020, 2021; El Kenawy et al., 2021; Mansour et al., 2021, 2022). However, none of these studies concentrated on investigating the link between the population concentration and the number of COVID-19 cases. For example, Al-Kindi et al. (2020) used several geospatial techniques within the GIS environment such as hot/cold spots analysis, weighted mean centre (WMC), standard deviational ellipses, and Moran's I autocorrelation coefficient to evaluate spatial distribution of COVID-19 over Oman. The final results showed that the following Wilayat such as Mutrah, AS Seeb, and Bowsher were the highest effected areas in Oman. Other studies tried to use socioeconomic and demographic variables to measure COVID-19 incidence rates in Oman (Al-Kindi et al. 2021; Mansour et al., 2021). Geospatial modelling with different socioeconomic indicators were applied to investigate any possible spatial associations of COVID-19 incidence. The results showed there were increased numbers of COVID-19 cases between migrant workers in the field of agricultural, health, and business especially in Muscat and Al-Batinah governorates but for the industrial sector the highest COVID-19 cases were in Wilayat of Al-Duqm and Salalah (Mansour et al., 2022). Remotely-sensed air quality data from MODIS was used to estimate the impact of COVID-19 in air quality during the lockdowns in 21 areas (including Muscat). Six main components of air pollution were examined (AOD, NO, CO, O3, NO2, SO2) (El Kenawy et al., 2021).

According to the Omani Ministry of Health (MOH) (https://covid19.moh.gov.om/), there have been more than 160,018 confirmed COVID-19 cases in Oman, with 1681 deaths from 3 January 2020 to 2 April 2021. (Al-Kindi et al., 2020; 2021). The exploration aims of this work is to spot the spatial distribution of COVID-19 in Muscat. It is also to verify any possible link between level of people concentration and COVID-19 spread The novelty of this study is to improve the procedures taken to combat the COVID-19 transmission in the unfortunate case of another breakout. The hypothesis of this study is built based on the approval of the positive and strong link between population concentration and COVID-19 cases.

Material and Methods

Study Area

As stated previously, the study area is based in the capital city of Oman (Muscat Governorate). Located in the northern part of the country, with a 300 km coastline including small islands being exposed to the sea of Oman. Muscat is found between latitudes 22° 50' 34" and 23° 38' 43" North and longitudes 58° 03' 34" and 59° 13' 29" East. The study area consists of six Wilayat within its border (Bawshar, AS Seeb, Mutrah, Al Amrat, Qurayyat, and Muscat) According to the 2020 census, Muscat has a total population of around 1.3 million, with an area of about 3797 km^2.

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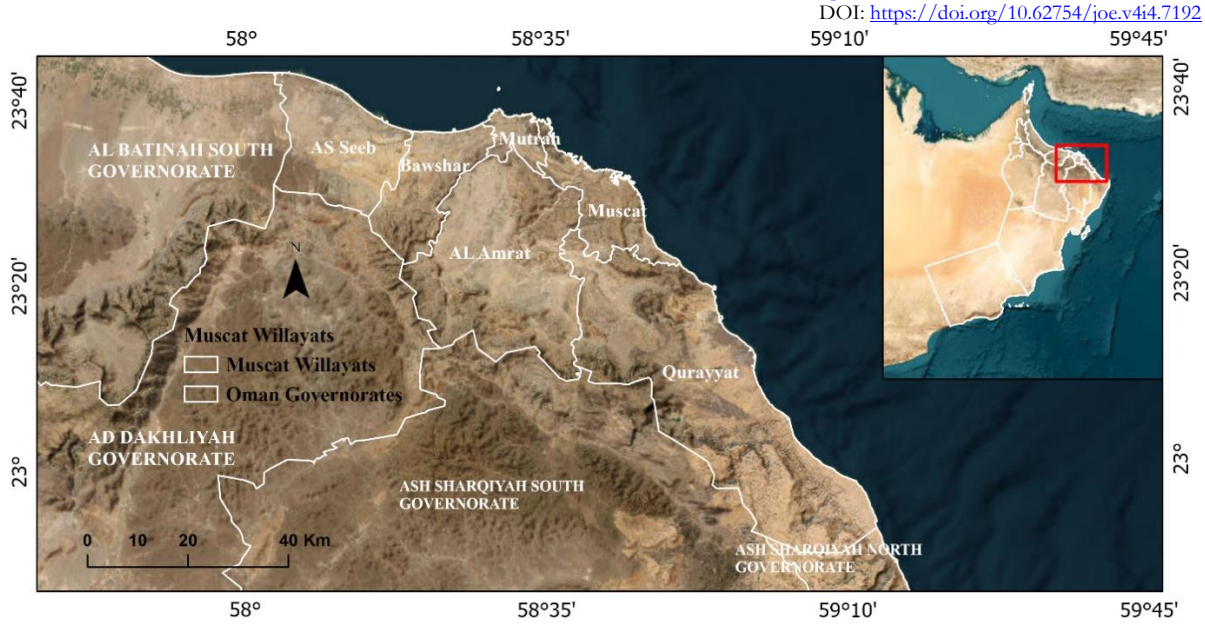

Figure 1: The Geographical Sitting of Study Area

Materials and Data Description

Table 1 summarises the spatial and non-spatial datasets used in this study. Spatial data include Muscat Government boundary, six Wilayat boundaries, and settlement locations. While non-spatial datasets include demographic data for each Wilaya, attributes of Wilayat, and settlements. UTM Projected Coordinates System (GCS_WGS_1984 Zone 40N) was used to keep all the spatial data consistent in one coordinate system.

Table 1. Dataset Layers' Descriptions and Sources

Component	Variables	Data type\ format	Sources
Spatial Data	Built-up area	Vector/Polygon	Oman National Spatial Data Infrastructure (ONSDI) http://nsdig2gapps.ncsi.gov.om/nsdiportal/
	Willaya Boundary		
	Governorate Boundary		
Non-Spatial	COVID-19 statistics	Excel file	Statistical department at the Ministry of Health
	Census data	Excel file	National Center for Statisyical & Information (NCSI) https://ncsi.gov.om/Pages/NCSI.aspx

There are three types of data that have been collected. The first data is about the population and area (total area) for each city (Wilaya) in Muscat. This data has been collected from the National Center for Statistics & Information (NCSI). Additionally, the statistical yearbook (2021) was downloaded from the website. The book contains the latest geographic data about all the Omani Wilayat. The second type of data collected (COVID-19 statistics) was acquired directly from the statistical department of the Ministry of Health. It contains the daily collection data for the number of corona cases in Muscat. GIS data has been collected from the Omani National Spatial Data Infrastructure (ONSDI) (Fig 2). Three types of data were obtained, the first one about the boundaries of each Wilaya as well as Governorate of Muscat, and the third about the built-up area.

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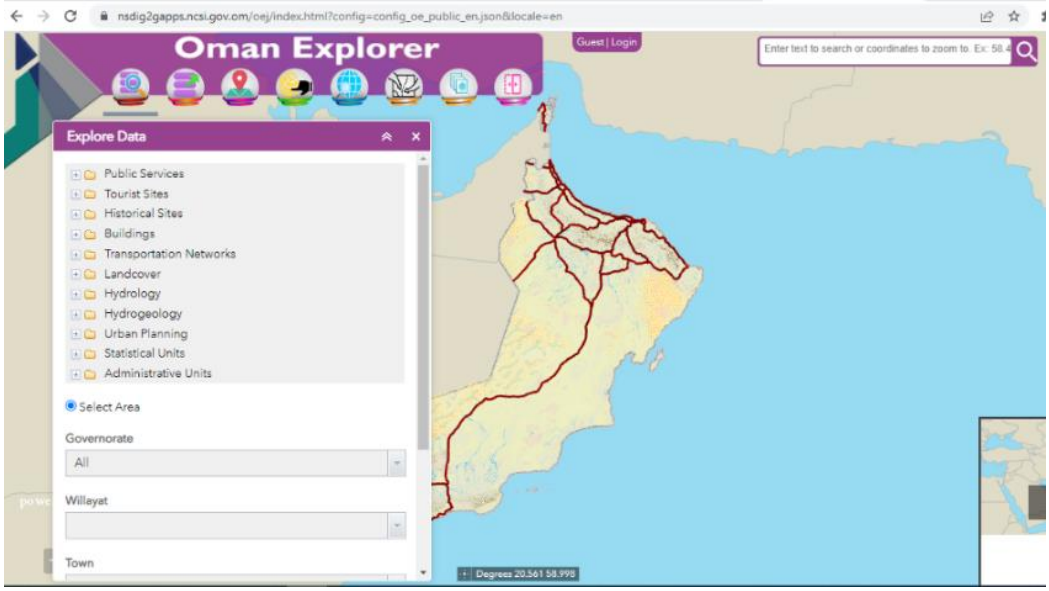

Figure 2: Snapshot of the Oman National Spatial Data Infrastructure website

Methods

Table 2 presents the two types of variables (dependent and independent) of this study while Table 2.1 presents controlled variables.

Table 2: Dependant and Independent Variables

Types	Variable	Units
Independent	Number of COVID-19 cases	Number of COVID-19 cases per city.
Dependant	The population density	Persons per km².

Table 2.1: Controlled Variables

Controlled variable	Why control this variable?	How to control?
Location: Muscat	It is important to get the data from one country, as different countries implement different procedures to decrease the spread of the virus, leading to skewed data. Moreover, I decided to choose all the cities from Muscat to keep my exploration consistent and eliminate any possibility of bias in the choice of cities. Additionally, the government locked out Muscat from all the other cities, during the pandemic so it would be logical to choose cities within Muscat only.	The 6 cities chosen to conduct the data collection procedure are in the capital city (Muscat).
Time	Many types of COVID-19 spread over different periods in Oman like Omicron, Alpha, Delta, and more. The outbreaks of these types of COVID-19 were all at different times. Additionally, these types of COVID-19 have a different rate of spread, which could alter the accuracy of the data collected. However, the data given doesn't specify the COVID-19 type.	The time chosen to collect the data will last from May 2020 to March 2021

There are many articles suggesting that governments are giving out inaccurate COVID-19 statistics (Galaitsi et al., 2021; Miller et al., 2022). According to a study conducted by the University of Washington in May 2021, coronavirus is claiming about 33 000 lives per day worldwide, while the numbers recorded by governments are half that number (IHME, 2021). Moreover, the only source available on COVID-19

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statistics at the level of Wilayat for Oman is given by the Ministry of Health. There is no other statistical data available that can be implemented. Therefore, we have no insight into whether the data given is accurate or not. To compete the work several procedures were implemented as follows

1. Acquire the COVID-19 positive tests in all 6 Muscat cities between 2020 and 2021.

2. Acquire the population size of all 6 Muscat Wilayat.

3. Acquire the total area of all 6 Muscat Wilayat.

4. Acquire the built-up area of all 6 Muscat Wilayat.

5. Calculate densities for general population (GPD) and built-up area population (BPD) of all 6 Muscat Wilayat.

6. Pearson's correlation coefficient is widely used to measure the relationship between two or more variables. The result determines the nature and strength of the association (Sciuva, 2024). Pearson's correlation coefficient was calculated in Excel.

7. Convert the data to percentages.

8. Make a Bar chart, showing the difference between the population density percentage (both BPD and GPD) and COVID-19 cases percentage in Muscat, for all 6 cities.

9. Link the COVID-19 cases table to GIS data (Wilayat Layers).

10. Analyse GIS data and create thematical maps (population and COVID-19 cases spatial distribution).

Results Analysis

Table 3 briefly presents the calculation of population density using two different methods regarding the number of COVID-19 cases in each Wilaya. This is done by dividing the population to total area for the general density (GPD), and the built-up area density (BPD). The last step taken was to convert the data into percentages. This was done to have all the numbers presented within the same scaling, as it would make it easier to look at when constructing a bar chart.

With the results having been converted into bar charts, it becomes much easier to identify the correlation between the percentage of COVID-19 and the percentage of population density. As seen from the bar charts (Fig 3), the percentage of COVID-19 had grown significantly with the increase in the Built-up Population Density (BPD) percentage. While this relationship was not as strong as using the General Population Densities (GPD) percentage, it becomes clear that using the built-up area in these calculations had made the results more reliable, as it gives a more accurate overview of the actual population density due to it only using the areas where people live in. However, Qurayyat and Al Amrat have a significantly higher BPD percentage than COVID-19 percentage, while it is the opposite in Bawshar and Al Seeb. This is due to the high availability of hospitals that provide COVID-19 tests in Bawshar and Al Seeb, while the availability in Qurayyat and Al Amrat is significantly lower. Evidently, figure 4 shows the number of public health units available in all 6 cities.

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Table 3: Calculations of Population Density with Percentage of COVID-19 Cases with the General and Built-Up Population Densities

Wilayat	COVID-19 Cases	Population	Total Area Km²	Built-up Area Km²	GPD	BPD	GPD%	BPD%
Mutrah	11093	231614	90.34	5.12	2564	45215	51.91	17.18
Bawshar	19226	383257	340.05	8.76	1127	43728	22.82	16.62
AS Seeb	26043	479893	488.85	11.48	982	41805	19.88	15.89
AL Amrat	4586	121344	1067.73	4.14	114	29297	2.30	21.53
Muscat	10059	31409	273.94	0.81	115	38620	2.32	14.68
Qurayyat	1290	58538	1535.74	2.58	38	22706	0.77	14.10
Total	72297	1306055	3796.65	32.89	4940	221371	100	100

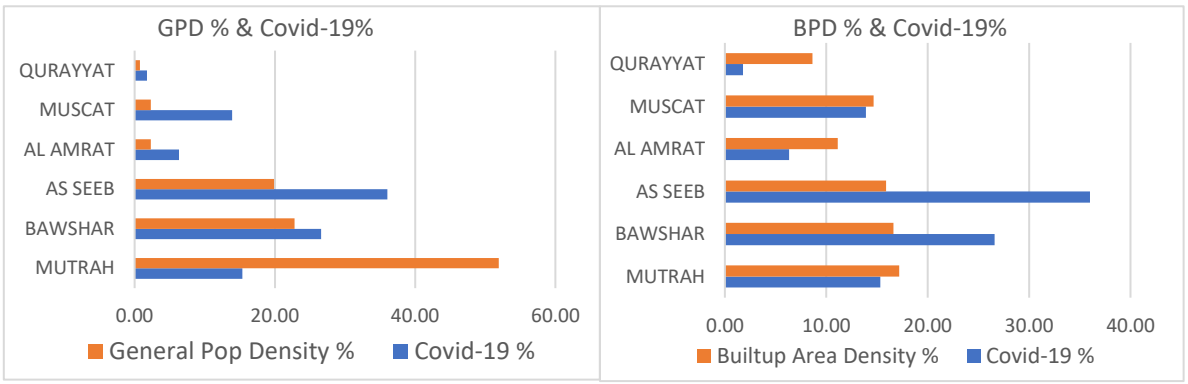

Figure 3: Bar chart showing relation between COVID-19% and two type of densities (General Density & Built-up Area Density)

Moreover, the transportation system in Bawshar and Al Seeb is much more advanced, as the road systems and amount of public transport are more developed. This causes the population of Bawshar and Al Seeb to have a higher tendency to take these tests, as it is easier to access. However, Mutrah contradicts these claims as its BPD percentage is significantly higher than its COVID-19 percentage, while it is seen to have the second most public health units in Muscat. The reason for this occurrence is unknown (further investigations are recommended).

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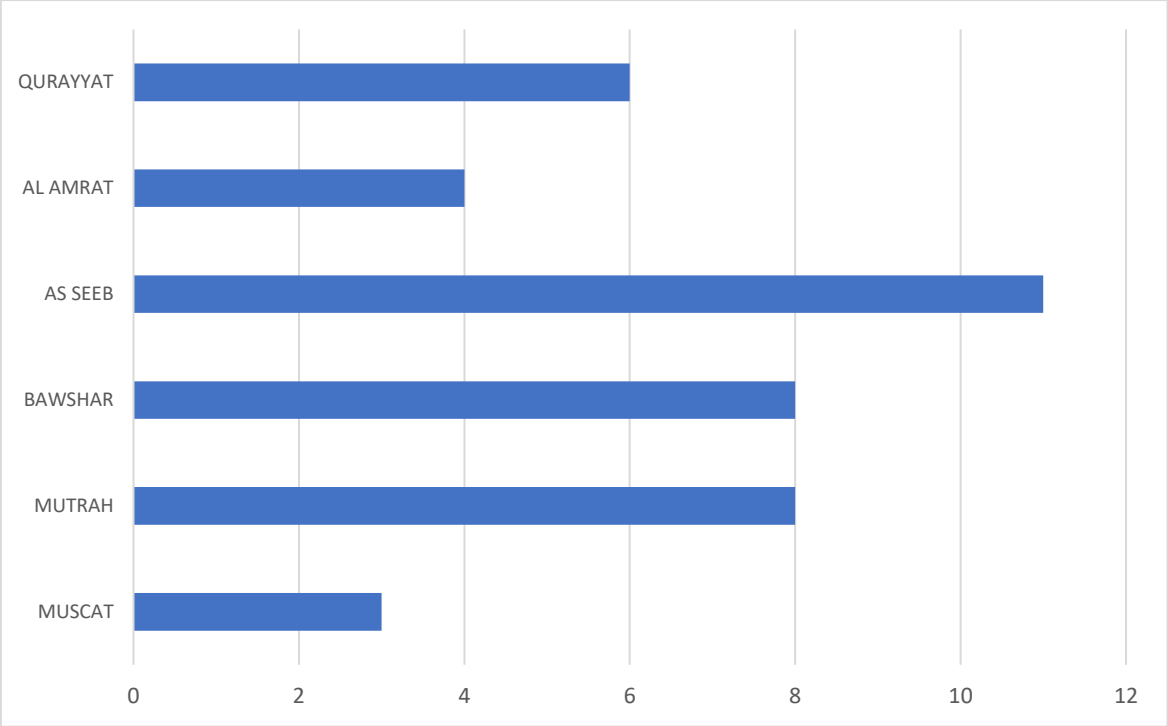

Figure 4: Number of public health units in all 6 cities

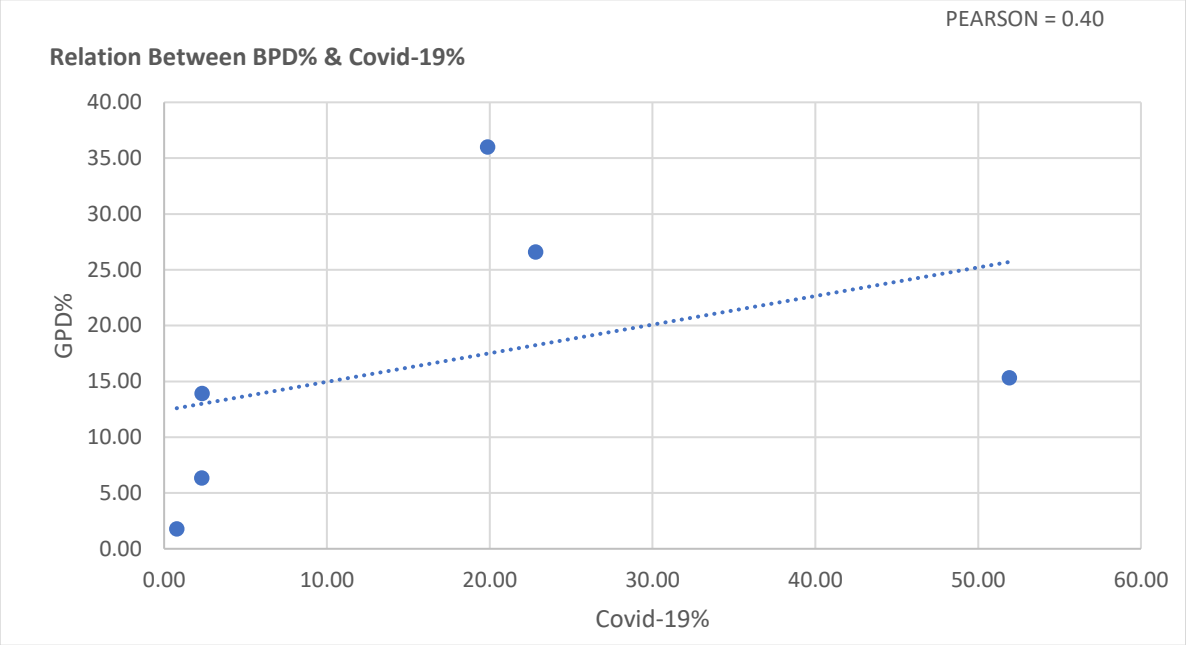

Figure 5: Correlation between COVID-19% and GPD%

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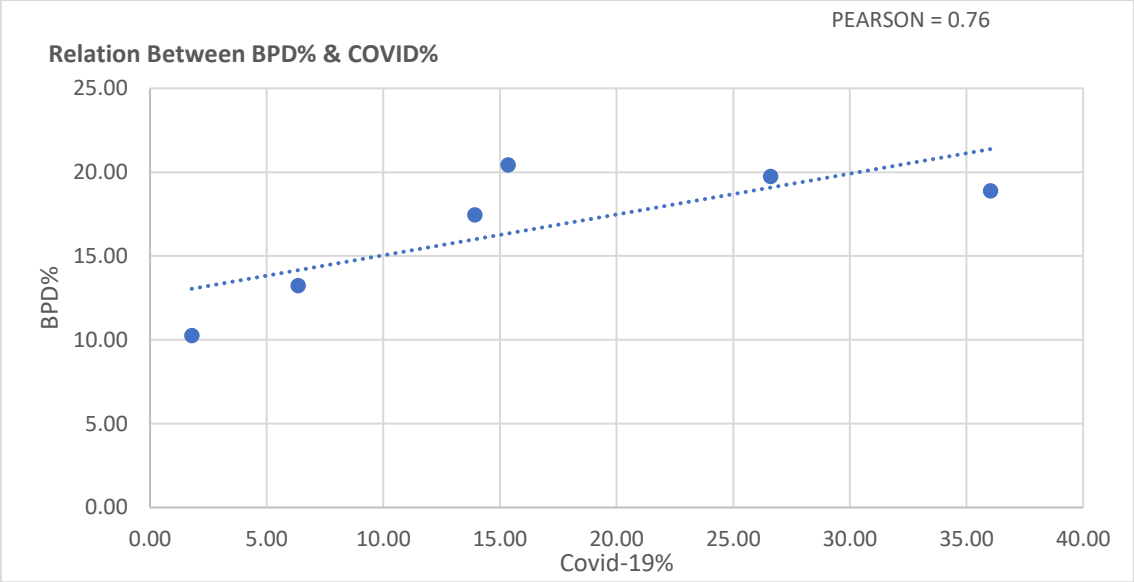

Figure 6: Correlation between COVID-19% and BPD%

Figures 5 and 6 have made it clear that there is a positive correlation between these two variables. However, the relationship is much stronger in Figure 5 with the correlation being measured at 0.76 compared to 0.40 in Figure 6. For better contrast, bivariate maps were used to approve the relation between variables. Bivariate maps are thematic maps whose characteristics are represented by the merging of symbols between two or more variables in a single map. The aim of these variables is to visualize the potential relationships between the variables that may not be apparent through a single variable map (Carstensen 1986; Nelson, 2020). For example, Figure 7 represents bivariate maps to find the visualized relation between population number and COVID-19 cases in the Governorate of Muscat. The figure shows that Bawshar, Al Seeb, and Mutrah have the highest populations and the highest number of COVID-19 cases. The other three Wilayat show dwindling population numbers and a smaller number of COVID-19 cases.

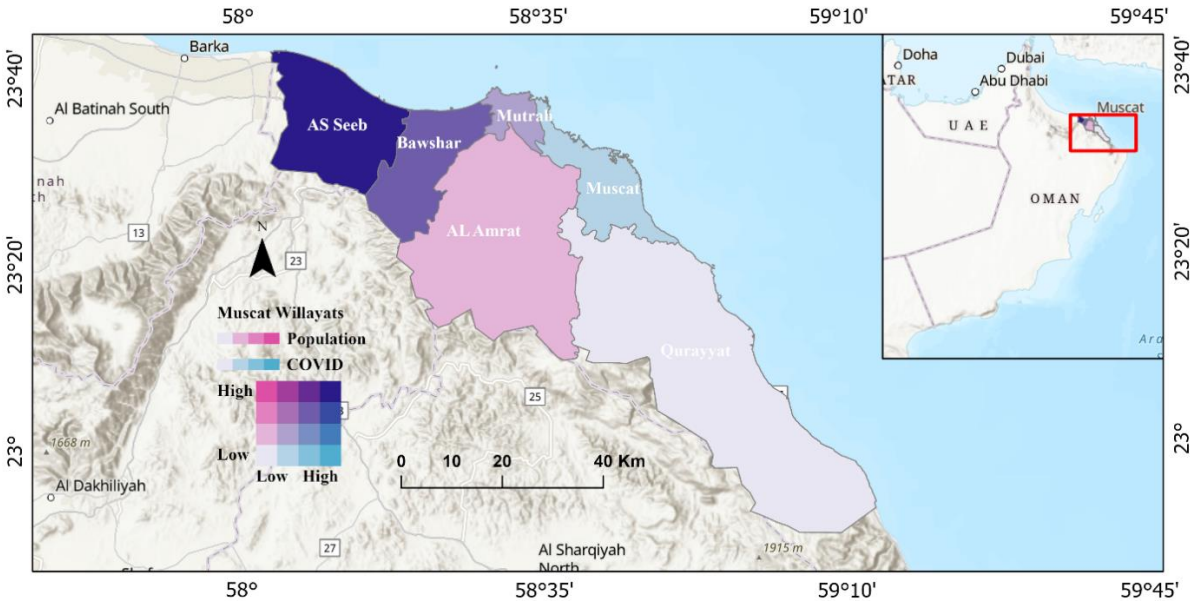

Figure 7: Bivariate map showing total population and total number of COVID-19 cases in each of the Muscat Wilayat

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Figure 8 displays the visual results of the correlation between COVID-19 cases with two types of densities: general area density and built-up area density. In comparison between figure 7 and 8, there is an agreement in the relationship, but seen more clearly in the built-up area. In this figure the six Wilayat can be classified into three levels: the first level is represented by the Wilaya of Al Seeb and Muscat, the second level is the Wilaya of Mutrah and Bawshar, while the lowest level is represented by the Wilaya of Al Amrat and Qurayyat.

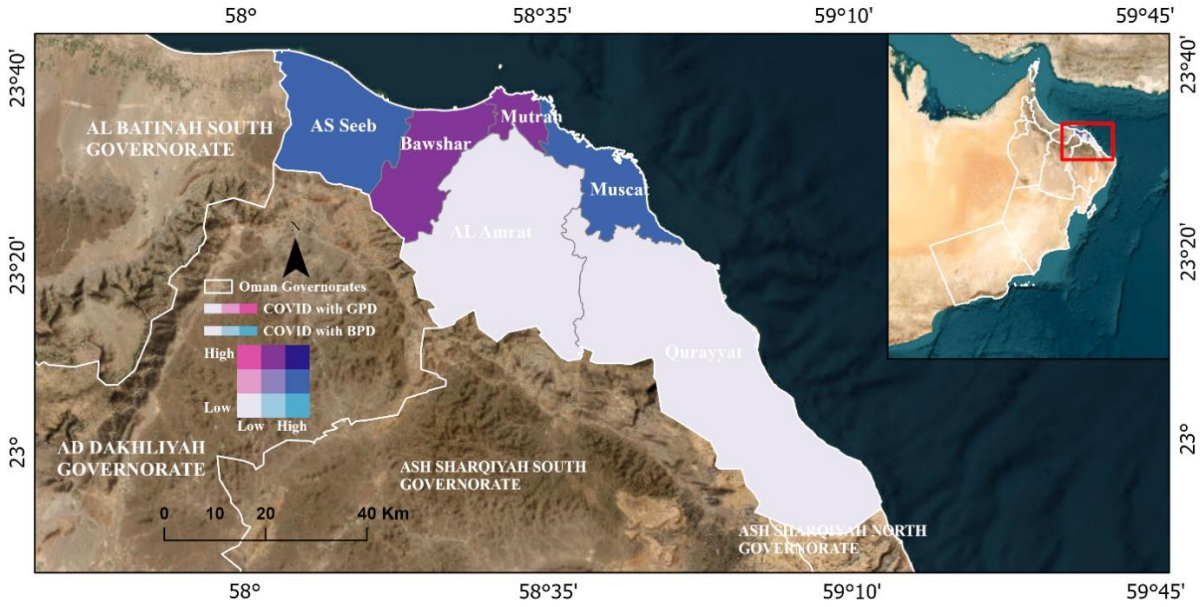

Figure 8: Bivariate map showing the links between population concentration and COVID-19 in both general area and built-up area densities

Discussion & Conclusion

The influence of socioeconomic issues, especially density, on the spread of coronavirus is one of the topics that has not been settled scientifically. Some scientists like Sciuva (2024) called it a debatable subject. However, the explanation of any possible relation between socioeconomic and coronavirus transmission are not straight forward task (Sharifi and Khavarian-Garmsir, 2020; Arif and Sengupta, 2021; Sciuva, 2024). These type relations could be biased and cannot be relied upon. It is a natural relationship between the number of population and the number of COVID-19 cases. It is expected to increase the COVID-19 recorded cases compared to the large population. The total number of COVID-19 registered cases depends of several factors such as availability and accessibility of test, cost of these tests. Socioeconomic factors especially in less developed countries and rural areas cannot be ignored, that delay the expansion of COVID-19 testing.

In this work, the hypothesis was built based on a positive link between the population concentration and the number of COVID-19 cases. Once data were collected and manipulated, the necessary calculations and data were hence turned into diagrams such as charts, graphs, and maps, which exposed the number of COVID-19 cases, within a certain population density. In this study the Pearson's correlation showed positive correlation with the value of 0.76 in built up densities compared to 0.40 in general densities. This means that the smaller areas with highly concentrated populations spread the COVID-19 infection much faster than the less concentrated populations.

Wilayat AS Seeb, Mutrah and Bawshar have the highest influence when it comes to population density and the COVID-19 transmissions in its area. These three Wilayat have the highest population numbers with the smallest area boundaries in the Governorate of Muscat. Wilayat Al Amrat and Qurayyat have the lowest population numbers with the largest area boundaries. Most of these areas are covered by mountains and deserts. However, with the Muscat Wilayat having some exceptional cases, it is evident that despite the

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population density being low, the number of COVID-19 cases is still high. The reason for this is that most of Muscat's Wilayat land is mountainous and deserted, as only 0.813 Km^2 of its total area (273.973Km^2) is built on and inhabited, indicating that Muscat Wilayat have a high population density, thus proving that the number of COVID-19 cases and the population density are correlated. Therefore, if another outbreak happens in the future, cities with higher population densities will see faster and more rapid spread of COVID-19 throughout their populations, leading to a higher number of cases and fatalities if nothing is done to stop this spread. This was helpful in outlining a connection that might possibly be exploited to lessen the consequences of a future breakout.

This study's results are consistent with several studies. Studies conducted by Arif and Sengupta (2021) in India used the same methods of Pearson's coefficient and Thiessen polygon to measure the influence of population density on the spread of COVID-19. The final results matched with current study that the surge of COVID-19 is strongly hinged by population density. Studies done by Boterman (2020) also found some positive interactions between a country's density and the infection rate of COVID-19 by employing correlation and regression models. Regression model was used to measure theses type of relations (Lin et al., 2020). Their results confirm the contribution of population density to the transmission of the Corona pandemic in China. This is what confirms the consistency with the study in Muscat. Nevertheless, Sciuva, (2024) did not find a significant positive correlation between population concentration and the spread of the virus in his comparison study between New York, London, Roma and Sao Paulo.

By taking measures to decrease overall population density, such as investing in housing outside of already large cities like Al Seeb and Bawshar or encouraging some portions of the population to relocate to a less densely populated area. This may certainly assist and prepare Oman or even other countries around the world in the event of another outbreak. This investigation explains not only why lowering the population density is crucial, but also why maintaining social distancing between each other is crucial. Through social distancing, one is essentially attempting to limit the number of people in a surrounding vicinity, in turn decreasing the population density of a specific area.

This work has many strengths, for example, the wide usage of charts, graphs, and spatial distribution maps made possible using advanced technology (GIS). The diversity of the result's presentation gives more variety in building the analysis. This gives a much deeper understanding of this study's exploration. An additional strength of this study was the method of calculating a population's density (total area, and the built-up area). By using the built-up area, which a was more accurate form of data, Muscat is now known to have many deserted and mountainous areas with insignificant populations. Furthermore, deserted land should not be used as an area when calculating the density of a city. Another strength of this exploration is that there are very few studies conducted on this issue, as the spread of this virus is still considered very recent, and the number of COVID-19 cases in specific cities within Muscat are not available publicly. Therefore, this exploration will significantly impact the community in raising awareness of this issue.

The weakness of this study is that the data was only available for a brief period between the 1st of May 2020, to the 4th of March 2021 for only six Wilayat (cities). Furthermore, if the data given was extended to longer periods and more cities, the results would be even more accurate. Additionally, the accuracy of COVID-19 tests is not at 100%. The accuracy of coronavirus detection tests conducted in specialized laboratories reaches 95%, while the percentage drops to 80% for home testing (FDA, 2021). This could have altered any of the results used. Another weakness is that the COVID-19 tests were taken from different organizations (government and private health centres). This could result in miscommunication between the organizations, that would cause the data to be inaccurate.

For better analysis and approval of the role of population concentration in the spread of COVID-19, mortality rates associated with the pandemic can be utilised. Data on the mortality rate would have been beneficial because the mortality rate will illustrate the severity of having high population densities, which will therefore help raise further awareness, and encourage governments to be more transparent with data on COVID-19 and make better policies to tackle this issue. Additionally, vaccination rates would further help the explanation of this study. Data on vaccination rates would have helped better understand the correlations that do not match with the hypothesis, as cities with a better human development index are

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bound to have higher vaccination rates which as a result lower COVID-19 cases. Therefore, a comprehensive study covering deaths associated with the corona pandemic as well as the vaccination rates are recommended. This type of study may prove the links between population concentration and COVID-19 spread. It could also help decision makers in health departments to improve the procedures to avoid this type of pandemic in the future.

Authorship Contribution Statement

T. A.: writing – original draft, reviewing final draft, methodology, visualization, formal analysis, and discussion. K. A.: review & editing, literature review, data collecting and visualization. H. A: writing – review & editing, data and results analysis

Declaration Of Competing Interest

The authors disclose that are family members. However, this relationship has not influenced the design, execution, or reporting of the research.

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