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A comparison study of an undisrupted versus a restricted viral transmission of Covid-19 using spatial simulations

by

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And finally, to my favourite person and my whole world, my daughter. Thank you for your patience and understanding when I had to work. You are my beginning, my end, and everything in-between.

Abstract

This research study applies an Agent-Based Model (ABM), to compare undisrupted and restricted transmissions of COVID-19 within two socio-economic diverse areas. This study explores the impact of population density, the use of public transport, and population age structure, on viral transmission. Two areas of varying socio-economic factors, within the city of Port Elizabeth, South Africa, were established. Sector A having a high population density of 12,655/km², primarily dependent on public transport, and having a large number of individuals under the age of 30. Sector B was selected for its low population density of 1,446/km², mostly dependent on private transport and having less individuals under 30 years of age. Three different scenarios of viral transmission were implemented within each area in a spatial simulation environment. An undisrupted transmission scenario allowed for 100% of agent mobility throughout the simulation. Two scenarios of restricted viral transmission were applied. A severely restricted transmission scenario allowed for 30% of mobile agents, representing essential mobility, while the remaining agents were confined to their residential buildings. Schools and non-essential building types were closed to reduce agent interaction. An 80% use of masks were applied to reduce transmission of the virus. A moderately restricted transmission scenario, allowed 70% of agent mobility during which schools were opened. An 80% use of masks was applied. For the purpose of of comparison between the sectors and related scenarios of transmission, each scenario was simulated until complete eradication of the virus occurred. Sector A eradicated the virus within 3.5, 4.5, and 6 months during undisrupted, moderately restricted, and severely restricted transmission scenarios respectively. Sector B eradicated the virus within 4.5, 5.5, and 10 months corresponding to undisrupted, moderately restricted, and severely restricted transmission scenarios respectively. Sector A eradicated the virus 20% faster within an undisrupted transmission scenario, 18% faster within a moderately restricted transmission scenario, and 40% faster within a severely restricted transmission scenario than Sector B. Sector A demonstrated a 5% decrease in population mortality during a moderately restricted transmission scenario, and a 10% reduction during a severely restricted transmission scenario. Sector B demonstrated a larger decrease in population mortality, with a reduction of 7% of deaths during a moderately restricted transmission scenario, and a reduction of 23% of deaths during a severely restricted transmission scenario. Population density and public transport thus demonstrated considerable impact on viral transmission, increasing the speed of viral transmission and reducing the ability to manage viral transmission. Population age structure was found to have a lesser impact on the transmission of COVID-19, as infections were largely encouraged within residential buildings.

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1. Introduction

The SARS-CoV-2 virus was first identified in Wuhan, China, in December 2019. From December 2019 until January 2022, more than 330 million cases of COVID-19 have been recorded globally. Of the confirmed cases, approximately 5.55 million cases were recorded as fatal (Worldometer, n.d.).

The SARS-CoV-2 virus relates to the family of viruses responsible for upper respiratory infections and shares similar characteristics to that of the SARS virus (SARS-CoV) of 2003 and the MERS virus of 2012 (Chen et al., 2020). The severe acute respiratory syndrome (SARS) outbreak, accounting for more than 8,000 confirmed cases and 800 fatalities, was eradicated by enforcing strict isolation measures, severely restricting the human-to-human viral spread (Wilder-Smith et al., 2020). On 23 January 2020, in an effort to restrict transmission of the SARS-CoV-2 virus, a travel ban was issued from and to Wuhan, the largest transport hub in Central China (Chen et al., 2020). However, the geographical extent of the spread far surpassed that of the SARS outbreak due to the rapid rate of transmission (Wilder-Smith et al., 2020).

Country-wide mitigation strategies were installed in an attempt to reduce the spread of viral infections as the mitigation procedures implemented by China succeeded in limiting viral transmissions of COVID-19 (Anderson et al., 2020). The level of mitigation strategies and the rates of limitation, however, differed as each country implemented strategies based on the health and economic capacities, the demographic structure, ideology, and its ability to maintain these mitigation strategies (Blakely et al., 2021).

Auchincloss and Diez Roux (2008) discuss the use of simulation models, particularly Agent-Based Models (ABM's) and System Dynamics Models (SDM's), to compliment traditional epidemiological investigation techniques used to investigate health patterns and the subsequent environmental effects. Simulation models aid in visualising the dynamic associations between the virus, the susceptible population, and the infectious population (Nguyen et al., 2020). Auchincloss and Diez Roux describe the ability of ABM's to apply vital interactions between heterogeneous entities and their diverse, physical and social environments (Badham et al., 2018), leading to the emergence of significant information not inferred by delimited traditional techniques (Beale et al., 2008). The use of Agent-Based Models thus depends on critical agent characteristics, reiterated by Clark et al. (2021). The created agents should display some level of autonomy, be diverse in their demographic characteristics, and should perceive and affect the social and physical environment described by the model. Modelling the characteristics and transmission of the virus spread is imperative to understanding current and future situations of the pandemic to effectively limit viral transmissions.

Several agent-based models have been developed to model the viral transmission of COVID-19, while numerous studies have been conducted using agent-based models to execute various mitigation strategies. The ABM, INFEKTA (Gomez et al., 2021) was used to prove a reduction in viral transmission after implementing a social distancing policy. Wallentin et al. (2020) used an ABM to demonstrate different intervention strategies in an attempt to control the transmission of COVID-19. Ferguson et al. (2020) use an ABM to describe the implementation of two different strategies in reducing COVID-19 mortality and its response on the healthcare system. These strategies consider mitigation of viral transmission via non-pharmaceutical interventions (NPIs), such as isolation and closure of schools and non-essential businesses; and the suppression of viral transmission through vaccines and medication. Truszkowska et al. (2021) use an ABM to discuss the importance of closing businesses and school, followed by the reopening of businesses and schools and the application of vaccine strategies. The ABM, COVID-ABS, was used by Silva et al. (2020) to investigate different social distancing strategies and discuss the various epidemiological and economic effects of each.

Several studies have focused on the impact of socio-economic factors on the spread of COVID-19. Bhadra et al. (2021) examined the association between population density and the mortality rate in India and found a moderate correlation between population density and the viral transmission of Covid 19. Sy et al. (2021) investigated the impact of population density on viral spread, using the basic reproductive number (R_0). It was found that the value of R_0 increased as population density increased, suggesting that the viral transmission of COVID-19 is impacted by population density. Kadi and Khelfaoui (2020) used the Pearson correlation coefficient to determine a relationship between population density and the number of infections, using data from the different cities of Algeria. A positive correlation was found describing a number of infected cases with an increase in population density. Additional studies (Carozzi, 2020, Ganasegeran et al., 2021, Wong and Li, 2020) found that population density is a driving factor in the viral transmission of COVID-19. A study presented by Sun et al. (2020) found no correlation between population density and viral transmission during strict lockdown measures.

The research study uses an Agent-Based Model to compare a restricted and an undisrupted transmission of COVID-19, with focus on the impact of three socio-economic factors in viral transmission. The impact of population density on the rate of the transmission of COVID-19, the significance of public transport in viral transmission, and the influence of the population age structure in viral spread, will be considered.

2. Problem Statement

The metropolitan city of Port Elizabeth consists of both high and low-income areas, of which poverty is significantly evident in low-income areas. Areas that fall within the low-income brackets tend to consist of unskilled manual labour of which employment may be on a monthly, weekly, or daily basis, forcing individuals to be constantly seeking income. Jobs are often found outside the area, requiring long travel distances. Most individuals within these areas rely on state support, and for many, it is the only source of income (Potts, 2012). In comparison, people within the high-income brackets, such as skilled professionals, have easier access to credit and can sustain their households for longer periods between employment. Low-income households are often overpopulated consisting of more than one family supported by a modicum income. Households within higher income brackets tend to be smaller in size.

The demographic structure within the low-income brackets, describes a younger population due to older age groups within these areas not sharing longevity of comparable age groups in higher income areas due to health, hygiene, and welfare. This accounts for older individuals in higher income areas as opposed to lower-income areas (Statistics SA, 2011). Most individuals within the high-income brackets have access to private health facilities through private transport. In comparison, individuals within the low-income brackets rely on healthcare from state hospitals or public clinics, where a lack of resources may exist for patient care (Maphumulo and Bhengu, 2019).

The first case of COVID-19 within South Africa was reported on the 3rd of March 2020. The country went into a nationwide lockdown starting with severe isolation procedures to reduce the transmission of the virus. Although the implementation of lockdown was necessary, challenges arose within different socio-economic areas, such as job loss and a lack of income within low-income areas. Although these mitigation strategies have since been removed, it is essential to understand these areas with respect to their varying socio-economic factors during different strategies of viral transmission.

3. Aims and Objectives

Aim:

To compare a restricted and an undisrupted transmission of COVID-19, within two socio-economically diverse areas (referred to as Sector A and Sector B in this research study), focusing on the impact of population density, public transport, and population age structure in the spread of COVID-19 within these areas, using a spatial simulation model.

Objectives

1. To utilise an agent-based model (ABM) to simulate the transmission of COVID-19
2. Establish two socio-economically diverse areas, referred to as Sector A and Sector B in this research study
3. Define and test the population and agenda parameters and weights within the ABM
4. Adapt the ABM to include:
    4.1. A public transportation network
    4.2. A leave of absence for a small proportion of the population within a state of symptomatic
    4.3. Reduce the successful contact rate for the environmental transmission of COVID-19
    4.4. A social distance aspect for functionality of the transportation network
5. To initiate an undisrupted versus restricted viral transmission of COVID-19 within Sector A and Sector B using the agent-based model
6. To explore the impact of population density, public transport, and population age structure and how they impact the spread of COVID-19

4. Materials and Methods

Two socio-economically diverse areas within the city of Port Elizabeth, South Africa, will be identified and subjected to an adapted agent-based model, COMOKIT. The model will be used to simulate the transmission of COVID-19 through a heterogeneous population within a spatial environment. This will allow for the comparison of specific socio-economic factors, and their influence on both a restricted viral transmission and an undisrupted viral transmission within each community.

Each area will be subjected to two different modes of viral spread, an undisrupted versus and a restricted viral spread. Undisrupted viral spread will be indicated by a viral spread through the population without mitigation strategies, such as lockdown strategies, social distance procedures or mask applications. Restricted viral spread will be indicated by a viral spread through the population with the implementation of mitigation strategies, such as lockdown strategies, social distance procedures and mask applications.

4.1. Data Preparation

Datasets describing the demographic attributes of the metropolitan, from 2011, were retrieved as accumulated geopolitical boundaries for the entirety of South Africa. Data from the 2011 census was used as the data was received in high detail, describing the demographic properties per electorate boundary for South Africa. The data was segregated to isolate the electoral boundaries, referred to as wards, for the city of Port Elizabeth. The data was formulated to describe relevant socio-economic factors per ward. These factors included the total population, the population density, the average annual income, the employment rate, the population age structure, and the percentage of the population owning at least one motor vehicle. The population density was calculated for each electorate boundary, using the total population within the boundary, and the boundary area per square kilometer.

Land-use data describing the zonal information per land-parcel was retrieved, prepared, and adapted, and used to the generate spatial entities of the model, representing the built environment of residential buildings, places of work, schools, shopping centers, parks, etc. The land-use parcels containing unclear or multiple land-use types were verified using Landsat imagery and Google Maps.

Additional spatial entities were generated to represent the public transport vehicles, namely minibus taxis and buses. Since the public transport system mostly operates along primary and secondary road types, the number of vehicles generated were randomized according to the number of primary and secondary roads located within the specific study area. Each additional spatial entity was created to scale, describing similar spatial properties of the relevant public transportation vehicles. Minibus taxis were generated with an area of $10m^2$, and buses were generated with an area of $30m^2$. The transportation entities are, therefore, considerably smaller in area compared to those of the built environment, representative of the spatial limitations within public transport vehicles and between the passengers.

4.2. Establishment of Sector A and Sector B

The metropolitan city of Port Elizabeth is situated along the Algoa Bay, of the southern coast of South Africa. According to the South African Census in 2016 the city has a population of approximately 1.2 million individuals (Statistics SA, 2016), with an area of approximately 1950 km^2 (SSI Engineers and Environmental Consultants, 2011).

Due to the distinctive geographical and economic clusters of the population, the city is an optimum setting for epidemiologically focused research. High- and low-income clusters characterise the city with varied population densities, age structures, economic differences, and transport options.

According to the Comprehensive Integrated Transport Plan (CITP) conducted in 2011, the population of Port Elizabeth makes use of both private and public means of transport. The public transport system makes use of minibus taxis and bus services. Of the public transport types, minibus taxis are a dominant mode of transport since they are more frequently available and affordable to the population, performing a crucial part of the public transport sector (Fobosi, 2013). According to the CITP (2011), 2347 minibus taxis and 408 buses were in operation throughout the metropolitan during 2011.

Walking and public transport are the dominant modes of transport in low-income areas. The use of public transport becomes more frequent as household income increases, with the population making use of minibus taxis and/or bus services. Walking often coincides with the use of travel via minibus taxis and bus services. Public transport is more affordable for individuals within low-income areas than in private transport. Owning at least one motor vehicle involves maintenance, insurance, and fuel expenses that may not be affordable to the individuals residing in low-income areas. Private transport is a more time-efficient form of travel and is more widely used in high-income areas since most individuals are able to own at least one motor vehicles.

Due to the vast differences in socio-economic factors between the wards, two main study areas, referred to as Sector A and Sector B, will be identified to better compare restricted viral transmission and undisrupted viral transmission. The sectors will be established by identifying substantially different socio-economic factors, with focus on population density, the dominant mode of transport and the population age structure. Since these socio-economic factors can be related to income bracket the area falls within, the employment rate and the average annual income will also be considered. The types of land-use found within the sectors will be discussed in relation to the population age structure for functionality of spatial simulation model.

Figure 4.2.1. describes the contrast in population density and area per ward. A substantial difference in population density can be seen in the area known as Ibhayi, where the population density is between 5900 and 13200 individuals per square kilometer. These wards are visibly smaller in area compared to the surrounding ward boundaries. The larger ward boundaries, (such as those towards perimeter of the city), are dedicated to farmlands which attribute to the smaller population densities.

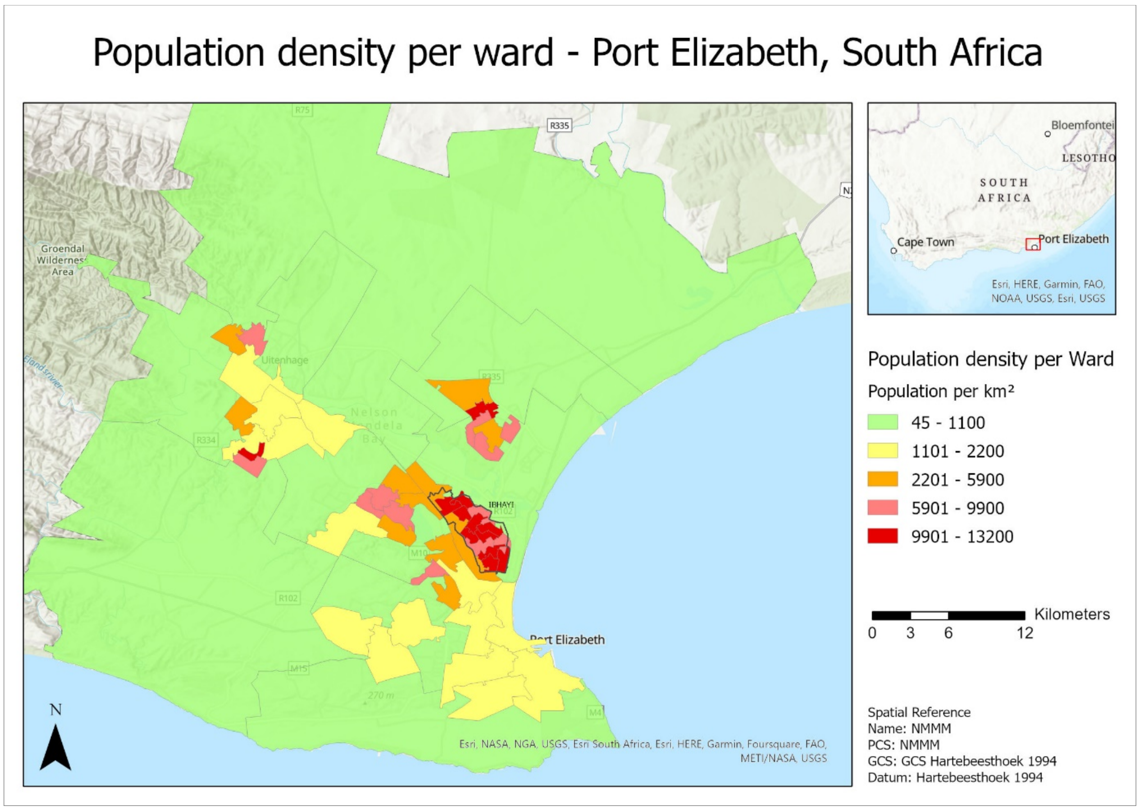


Figure 4.2.1: The population density distribution for the city of Port Elizabeth, South Africa. The population density was calculated using the 2011 Population Census data (Open Africa, 2017)

Figure 4.2.2 illustrates the percentage of the population per ward, that own at least one motor vehicle, constituting the use of private transport. As the figure describes, at least 80% of the population residing within the southernmost wards, have the means to rely on private transport; while less than 20% of the population residing within the northernmost wards, have the means to rely on private transport.

For the purpose of the spatial simulation model, it is assumed that the population per ward that do not own a motor vehicle, rely on walking and public transport, i.e., busses and minibus taxis. With the use of Figures 4.2.1 and 4.2.2, two study areas are established and will be referred to as Sector A and B. The additional socio-economic factors used to select the sectors, population age structure, the employment rate, the average annual income, and land-use, will be discussed in the sections below. An additional comparison of Sector A and Sector B will also be discussed.

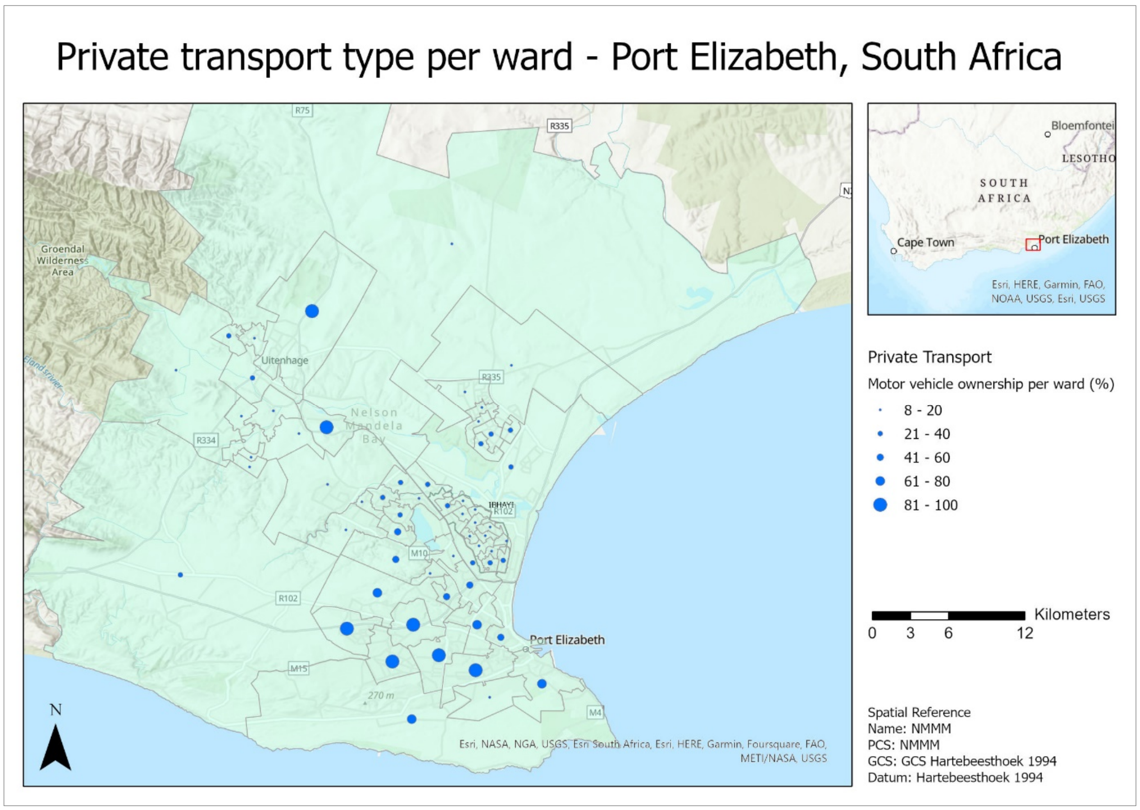


Figure 4.2.2: The percentage of motor vehicle ownership per ward for the city of Port Elizabeth, South Africa. described using the 2011 Population Census data (Statistics SA, 2011).

4.2.1 Sector A

Sector A is characterized by high population density of 12 655 individuals per square kilometre. The sector is comprised of one electoral boundary, specifically Ward 22, and additional commercial land-use types, located within the area known as Ibhayi. It covers an area of approximately 1,23 km² with a population of 15 583, according to the 2011 Census (Open Africa, 2017). Figure 4.2.1.1 describes the population age structure in relevance to the COVID-19 mortality rate as formulated by the

Woldometer (2020) during early onset of the pandemic. As illustrated, the sector consists primarily of younger individuals of schooling age (zero to nineteen years) and early working age (twenty to twenty-nine years). The mortality rate across the ages of zero to forty-nine years is significantly lower in comparison to the ages of seventy and onwards. The population number drops significantly from the age of sixty years. The population aged seventy years and above, constitute approximately 5% of the total population of Sector A.

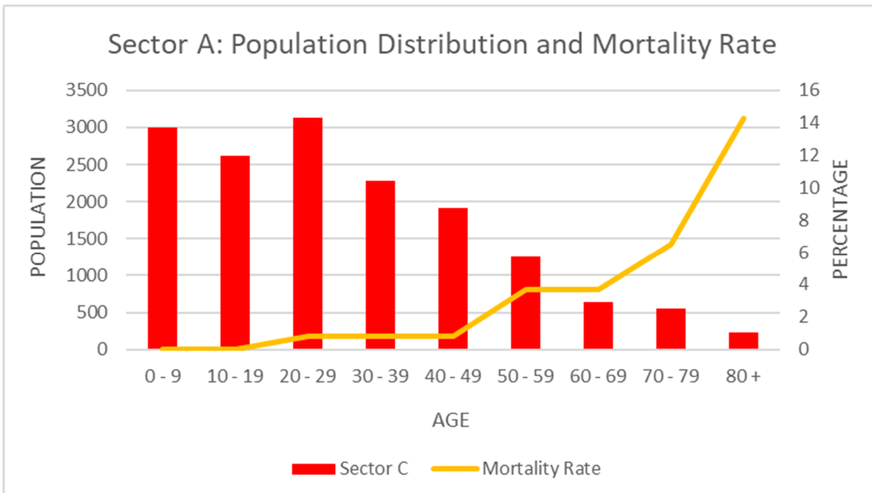


Figure 4.2.1.1: The decadal age distribution of the residents within Sector A in comparison with the mortality rate per age group. The data was derived from Open Africa (2017) and Woldometer (2020).

Of the population, 26% of individuals are employed while 40% are unemployed. The remaining 34% of the population are not of economic age. The average annual income in 2011, for Sector A, was recorded as R30,000. Of the ward's population, 14% own at least one motor vehicle, suggesting that the predominant type of transport within the ward is public transport by means of busses and minibus taxis. Figure 4.2.1.2 illustrates Sector A and the land-use types within. As seen in Figure 4.2.1.2, there is an abundance of residential buildings to accommodate for the high population density. Numerous open spaces and parks are apparent with few dedicated sports fields. The sector is comprised of eight schools offered to 5610 individuals, suggesting one school for every 702 individuals. Within Ward 22, only one shopping centre was available to cater to the entire population within. Additional commercial land-use types are incorporated into Sector A to ensure enough space for agents within the spatial simulation. Reduced spatial area for activities may affect the results. The minibus taxis and bus services created are present in Figure 4.2.1.2.

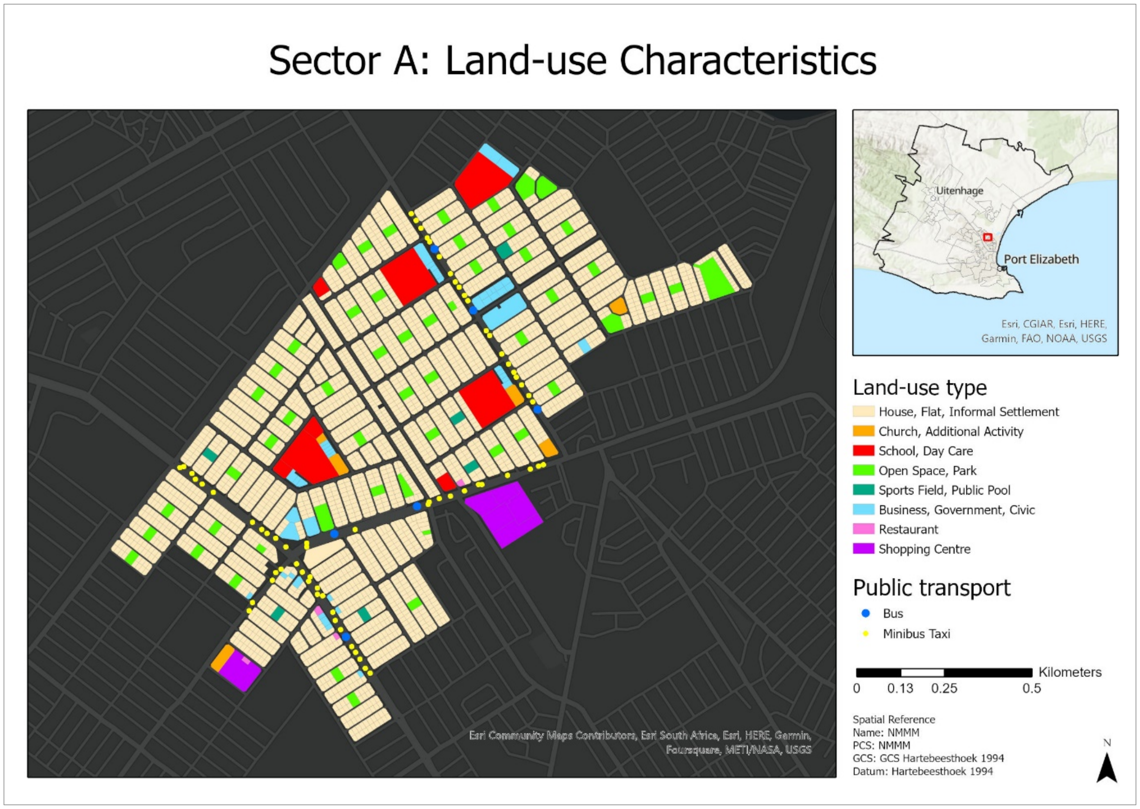


Figure 4.2.1.2: The land-use characteristics that constitute Sector A, within the metropolitan city of Port Elizabeth, South Africa. Sector A is represented within a spatial scale of 10 000 meters. The data was derived from Nelson Mandela Bay Municipality and Town Planning (2022).

4.2.2 Sector B

Sector B is selected due to its contrasting socio-economic factors, apart from the total population. Similar to Sector A, it has a population of 15 866. A similar number of individuals is required to ensure an equal viral transmission throughout each ward. In contrast to Sector A, Sector B is characterized by a low population density of 1446 individuals per square kilometre. The sector is comprised of one electoral boundary, identified as Ward 9, and covers an area of roughly 10,97 km² (Open Africa, 2017). Figure 4.2.2.1 illustrates the population age structure in relevance to the COVID-19 mortality rate as formulated by the Woldometer (2020). The sector consists of a higher number of individuals within the age category of forty to forty-nine years. The mortality rate across the age groups from seventy and onwards increases significantly. The population aged seventy years and above, represent approximately 10% of the total population of Sector B.

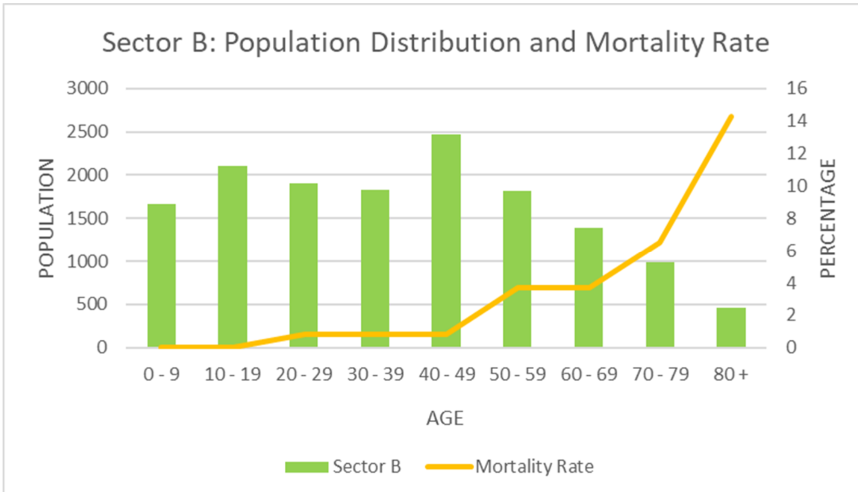


Figure 4.2.2.1: The decadal age distribution of the residents within Sector B in comparison with the mortality rate per age group. The data was derived from Open Africa (2017) and Woldometer (2020).

The rate of unemployment within Sector B is 5%, while the employment rate is 65%. The percent of the population not economically active is 30%. The average annual income, according to the South African 2011 Census, for Sector B was R117,000. The sector mostly relies on private transport, with 90% of the sector's population owning at least one motor vehicle. Figure 4.2.2.2 describes the land-use types for Sector B. As illustrated in Figure 4.2.2.2, numerous parks, open spaces, sports fields and public pools are available. Shopping centers are frequent, located within a radius of 1,5 km. More shopping centers are available in comparison to churches. Three church land-use types can be identified while seven schools are available to approximately 3778 school-going individuals, indicating one school for every 539 individuals.

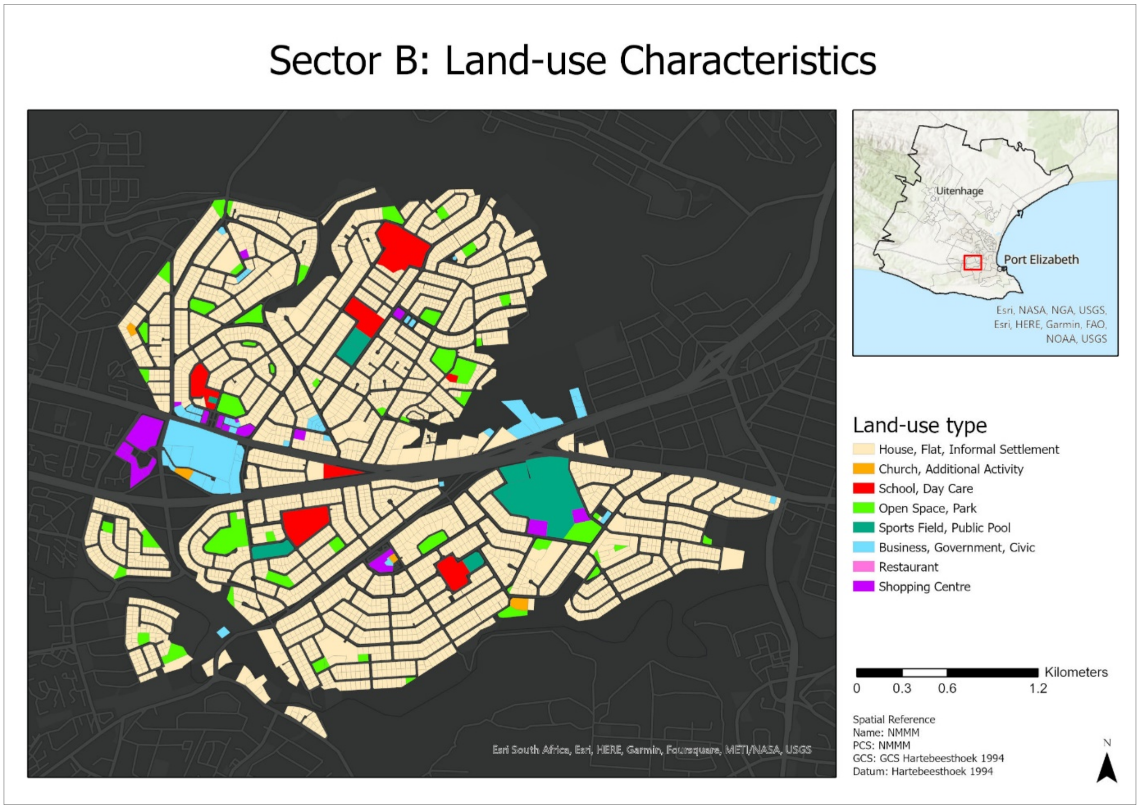


Figure 4.2.2.2: The land-use characteristics that constitute Sector B, within the metropolitan city of Port Elizabeth, South Africa. Sector B is represented within a spatial scale of 25 000 meters. The data was derived from Nelson Mandela Bay Municipality and Town Planning (2022).

4.1.3 Comparison of Sector A and Sector B

Sector A is considered within the low-income bracket. This is evident by the high population density describing over population and large households. The fewer number of individuals within the older age groups may be due to the lack of health and welfare within the area. Individuals within this area rely on healthcare from state hospitals and public clinics, where there is a lack of resources for patient care (Maphumulo and Bhengu, 2019). The population of Sector A rely significantly on walking and public modes of transport. This suggests an inability to afford private transport and is apparent by the low average annual income and the high unemployment rate. The unemployment percentage of 40% signifies unemployment of 6233 individuals within Sector A.

In comparison to Sector A, Sector B consists of a larger area with a significantly lower population density. Sector B is considered within a high-income bracket. The total population consists of more elderly individuals when compared to the number of elderly individuals within Sector A. The longevity of Sector B can be validated by the population within Sector B being able to afford private healthcare and thus having access to private clinics and hospitals. With a higher average annual income, households can afford to own at least one motor vehicle. Of the population, 90% own at least one motor vehicle. It is assumed that Sector B relies primarily on private transport which is evident by a higher average annual income and a significantly lower unemployment rate in comparison to Sector A. Of the 15 866 individuals within Sector B, 793 individuals are unemployed.

Figure 4.1.3.1 illustrates the number of land-use types for both Sector A and Sector B, excluding residential land-use types. Sector A consists of 3127 residential types, while Sector B consists of 3867 residential types. For the purpose of the study, both sectors were required to consist of a similar number of land-use types to ensure accurate study results.

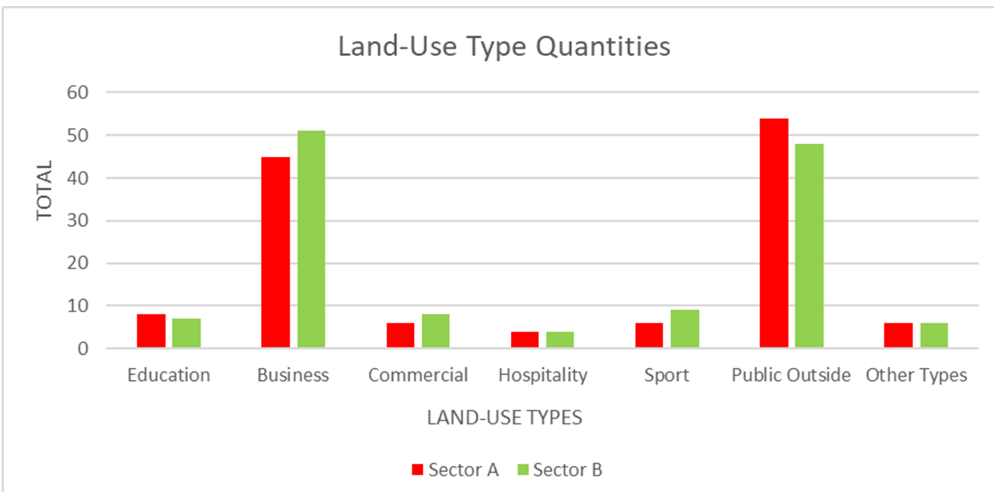


Figure 4.1.3.1: The number of land-use types comprising of Sector A and Sector B. Residential land-use types were excluded due to the large quantity. The data was derived from Nelson Mandela Bay Municipality and Town Planning (2022).

Population density is considerably higher in Sector A. The land parcels, representing the various building types, are spatially smaller in Sector A. The average spatial area of residential land parcels within Sector A is 236 m², and 1432 m² in Sector B. This illustrates an increased population density within each land parcel for Sector A.

The significant differences in the socio-economic factors discussed, renders Sector A and Sector B adequate study areas for the impact of population density, transportation type and population age structure in the spread of COVID-19.

4.3. Foundation of the Agent-Based Model, COMOKIT

The agent-based model (ABM), COMOKIT, is used for the study as it allows for the implementation of personalized data and the development of new actions. COMOKIT is implemented using the spatial simulation application platform, GAMA. The agent-based model has the ability to synthesize a detailed population with the use of adjustable population parameters. The adjusted parameters produce the required population number, the percent of males to females, the percent of unemployed individuals and the population's approximate age structure. COMOKIT uses the number of residential land-use types to assign the number of households present within the spatial simulation. The specified population parameters define the number of adults and children per household.

The additional land-use types, such as those categorized as businesses, schools, or open spaces, are used to assign activities. Activities can be described as the theoretical act being done by the agents, such as working, being in school, shopping or visiting friends, within the specified buildings. An agent can perform a number of agendas throughout each day. The set of activities carried out during the day is referred to an agenda. Activities are performed by entering the particular building and remaining within the building for the designated time. While agents perform the assigned activities, interaction with nearby agents can occur in the form of close spatial distance. During these interactions, as well as being within the same building as an agent infected with COVID-19, susceptible agents are at risk of contracting the virus.

The individual agents are autonomous and carry out work and school related activities based on their age, gender, the time of day, and the day of the week. Other activities are carried out based on parameter weights per building type, as well as the age and gender of the individual agents, and the time of day. For example, an individual female agent of 36 years of age, that falls within the employed population percentage, will carry out the working activity between 8am and 5pm from Monday to Friday. After 5pm during the week, the agent may carry out the activity of shopping or visiting a neighbour or friend. On Saturdays and Sundays, the agent autonomously selects a number of activities based on its age and gender. Female agents might prefer the shopping activity, while male agents might prefer a sporting activity. These preferences are defined by modifying the activity weights to suit the age and gender groups.

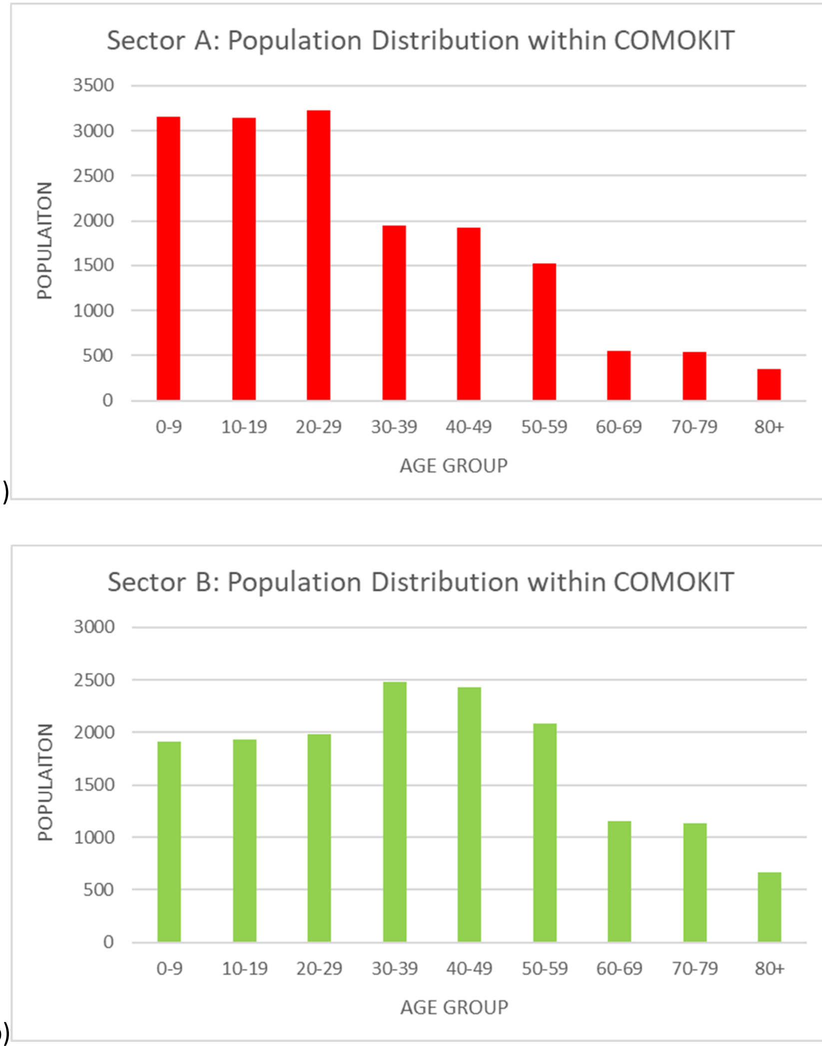
Although the spatial simulation is subjective to a specific area, agents are permitted to travel outside the spatial boundary of the area. The measure of authorization is specified from the agenda parameters.

4.3.1. Defining parameters and weights within COMOKIT

To identify the impact of population density, public transport, and the population age structure in the spread of COVID-19, Sector A and Sector B created within COMOKIT are required to resemble the diverse socio-economic factors. This is done by defining the specific parameters and weights featured within the agent-based model, COMOKIT.

Parameters are the quantitative adaptations used to define functional characteristics of the spatial simulation model, while weights are used to enhance the priorities and choices made by the spatial simulation. The parameters are categorized into population parameters (Appendix A), agenda parameters (Appendix B) and epidemiological parameters (Appendix C). Population parameters define the parameters used for the generation of the population. The agenda parameters are used to define certain properties of the daily agendas, such as the start and end times of work and school activities. Epidemiological parameters define the transmission dynamics of COVID-19 within the spatial simulation, such as the rate of successful infection, or the percentage of agents, per age group, at risk of death from COVID-19 infection.

Appendix A describes the population parameters used to generate the population within COMOKIT for Sector A and Sector B. Figure 4.3.1.1(a) and Figure 4.3.1.1(b) describe the population age structure of Sector A and Sector B, respectively, generated within COMOKIT using the synthetic population capabilities and defining the population parameters. Figure 4.3.1.1(a) describes a primarily younger population, consisting of agents between the ages of zero and twenty-nine, with considerably fewer agents being created within the sixty and onwards age groups. Figure 4.3.1.1(b) describes a population of agents mostly within the age groups of thirty to fifty-nine. In comparison to Figure 4.3.1.1(a), twice as many agents within the age groups of sixty and onwards were created. The population age structures for Sector A and Sector B, generated within COMOKIT, resemble the population age structures defined by the South African Census of 2011.



(a)
(b)

Figure 4.3.1.1: The decadal age distribution of the agents within Sector A. The population data was generated using the synthetic population capabilities defined by the population parameters within the agent-based model, COMOKIT.

The population generated for Sector A is approximately 16 354 agents, while Sector B has a population of approximately 16 256 agents. Since COMOKIT generates a population cased on the population parameters as well as the number of residential land-use types provided, the number of agents created per household size could be extracted. Figure 4.3.1.2 illustrates the number of agents created within the defined household size. As illustrated, Sector A consists primarily of households of eight or nine relatives while Sector B consists mostly of households of five or six relatives. COMOKIT combines three generations within one household, suggesting agents within the age groups of sixty and onwards, are generated within the households of agents aged sixty and younger, adding to the large household sizes. The large household sizes of Sector A are suggestive of the high population density seen from the sector, which can be attributed to overpopulation commonly observed in low-income areas.

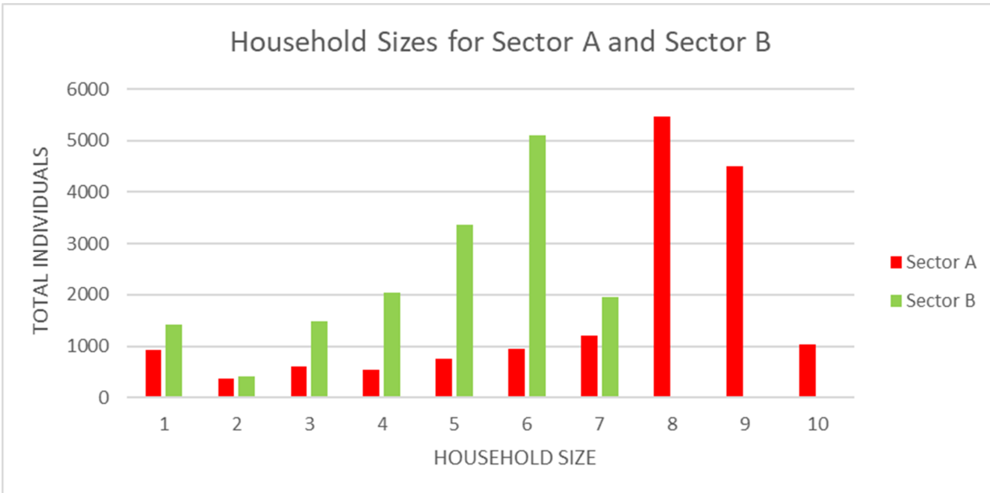


Figure 4.3.1.2: The total number of agents generated for the defined household sizes. The household sizes were generated using the synthetic population capabilities defined by the population parameters within the agent-based model, COMOKIT.

Appendix B describes the agenda parameters used for both Sector A and Sector B. The agenda parameters are used to define certain properties of the daily agendas, such as the number of days that are considered working and schooling days. Additionally, the agenda parameters specify the number of agents executing a certain activity together, in other words, it defines the number of individual agents within the social groups. The social groups can be reflected by colleagues or peers within a work or school environment respectively, or by predetermined neighbours and friends of the individual agents. The predetermined social groups of the individual agents, promote viral transmission within the spatial simulation. For instance, transmission of COVID-19 will be higher between peers within a school or between colleagues at work. The viral transmission rate is higher between social groups, and lower between the infected agent and additional agents located within the same building (Brugière et al., 2020). The agenda parameters define the number of activities a school going or working agent performs during working days of the week and over non-working days of the week. Agents classified as unemployed or retired are also permitted a maximum number of activities depending on the day of the week. The probability to travel outside the sector boundary was adapted according to the sector. Sector A has a high rate of unemployment, encouraging travel outside the boundary represents unemployed individuals seeking employment. A higher parameter quantity is therefore given to the probability of outside travel for Sector A.

In addition to the agenda parameters, the activity and building-type weights alter the preferences of agents towards specific activities and building types. The activity and building-type weights are modified to suit the socio-economic factors for each sector. Each weight is created according to the age and gender of the agent, based on the priorities of individual agents. Since Sector A is identified as a low-income area, and Sector B is identified as a high-income area, it can be assumed that the priorities differ between the sectors.

The weight of activities for Sector A are considered higher for outdoor activities and visiting family members and neighbours, rather than shopping or leisure activities, such as going to the cinema or a game center. Inessential shopping and leisure activities are costly, rendering these types of activities a low priority for Sector A. Building-type weights are assigned to specialized buildings, such as churches and community centers. Like the activity parameters, these weights are prioritized according to the age and gender of the agents. Agents grouped within the younger ages have higher building-type weight values for parks or open spaces, while agents within the older age groups have higher building-type weight values for community centers or churches.

Sector B is identified as a high-income area and the activity weights for indoor activities are prioritized depending on the age and gender of the agents. Such that agents classified in the younger age groups prioritize leisure activities, while agents within the age groups of twenty to sixty, and classify as female, prioritize shopping activities. Appendix D and Appendix E illustrate the activity and building-type weights for Sector A and Sector B respectively.

Appendix E lists the epidemiological parameters used to define the viral transmission dynamics within COMOKIT. The epidemiological parameters are defined for the original COVID-19 strain and no variants of the virus were considered for this research study. Two modes of viral transmission are achieved within the spatial simulation model, viral transmission between two agents, or the viral transmission from the current building to an agent. This type of transmission will be referred to as environmental transmission, and represents fomite transmissions. Fomite transmission describes infection via a contaminated object within a building. Brugière et al. (2020), cautioned the transmission rate within buildings as at the time of development, as literature pertaining to fomite transmissions was limited. Goldman (2020) and Goldman (2021) argue that COVID-19 transmission from fomites have previously been overemphasized during studies dedicated to the survival of the infection on surfaces and objects. The parameter for the successful contact rate within a building is thus reduced to half the fixed parameter value for the human contact rate. A duplicated human-to-human contact parameter value would imply that each agent entering a building laden with viral load, would have the same exposure probability as agents exposed by fellow agents. This concept would indicate an overestimated risk of infection via laden buildings.

The probability to infect other agents, depends on the adaptable parameters and reduction factor. Two adaptable parameters affect the successfulness of viral transmission. The human-to-human transmission parameter affects the successfulness of viral transmission from one agent to another. The environmental transmission parameter affects the successfulness of viral transmission from a viral load released into a building, to an agent.

The possibilities of agents requiring further treatment, such as hospitalization or intensive care, are denoted by fixed parameters dependant on the individual agent's age. COMOKIT negates the effect of an agent's gender on transmission dynamics within the spatial simulation. (Gaudou et al., 2020).

Apart from the parameters used to define the successful contact rate of environmental infections, the values of all epidemiological parameters remained unchanged for the purpose of this study. The parameters defined within this section were altered accordingly, considerably tested and approximately fitted to the accumulated socio-economic information.

4.3.2. Viral transmission and clinical states within COMOKIT

COMOKIT describes two modes of viral transmission: human-to-human infectivity and a viral load released within a building, referred to as environmental transmission. According to the ODD description of the COMOKIT model (Brugière et al., 2020), infection via buildings represents infection resulting from fomite transmissions.

Each individual agent is identifiable by a clinical state that is dependent on the infection dynamics within the simulation. The clinical states are defined by a modified Susceptible, Exposed, Infected, Recovered (SEIR) compartmental model. Figure 4.3.1.1 describes a simplified compartmental model constructed using the modified SEIR and hospitalization models defined by Brugière et al. (2020).

Figure 4.3.1.1 illustrates the clinical states, susceptible (S), latent (L), some form of infected (I_A, I_S, I_P), recovered (R), or the possibility of death (D). A probability of needing hospitalization (H_N) or intensive care (H_I) is depicted in the figure. Once infected, an individual has a possibility of moving to an asymptomatic (I_A) state, while presymptomatic (I_P) individuals have not yet transitioned to a symptomatic (I_S) state. A susceptible clinical state can be defined an agent at risk of infection from COVID-19. Brugière et al. (2020) describes the latent clinical state as the time between being exposed to the virus an becoming infective. An infectious clinical state describes an agent that has become infected by the virus and is able to infect others.

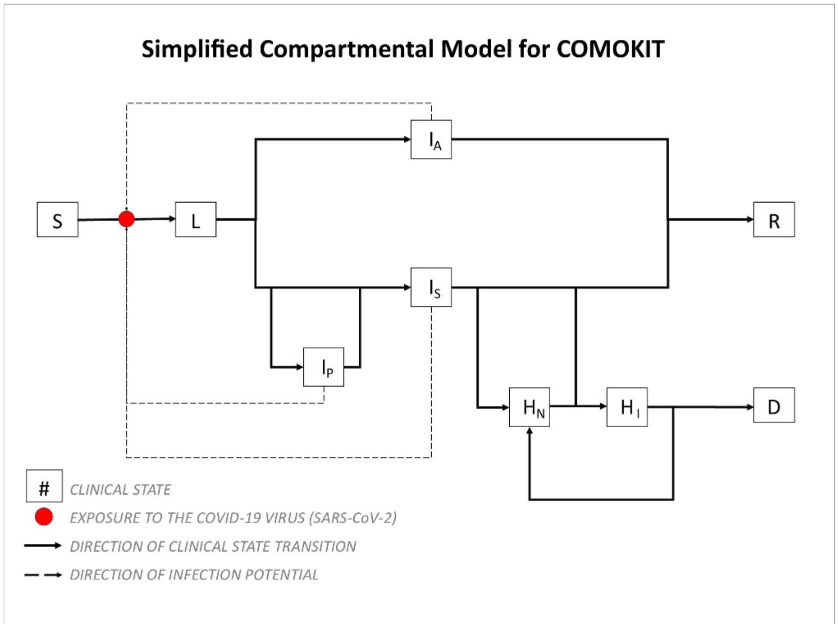


Figure 4.3.1.1: The simplified compartmental model describing the clinical states and infection dynamics of COVID-19 within the epidemiological model, COMOKIT. The simplified compartmental model is based on the modified SEIR and hospitalization models defined by Brugière et al. (2020).

An asymptomatic clinical state describes agents that are infected without any symptoms of COVID-19. A presymptomatic clinical state is the period in which agents are infected with COVID-19 but are not yet showing the symptoms. A symptomatic clinical state describes agents that are infected with COVID-19 and are showing symptoms of illness related to the viral infection. Asymptomatic agents have a decreased probability to infect others, in comparison to symptomatic agents. Being in a state of recovery describes an agent that has recovered from a COVID-19 infection and is no longer infectious. The clinical state of dead applies to agents that have not recovered from a COVID-19 infection and are removed from the spatial simulation. Agents in a clinical state of needing hospitalization and/or intensive care, are agents that have been infected by the virus and require medical assistance in an attempt to recover from COVID-19 infection. The clinical states and infection dynamics represented in Figure 4.3.1.1, are further explained by the viral transmission within the spatial simulation and simulated agents.

Once a susceptible agent is exposed to the virus, via human-to-human transmission or environmental transmission, the agent becomes infected with the virus and enters into a state of latency. The latency time period is calculated given the infected agent's age together with the incubation period. The incubation period is time between exposure to the virus and symptom onset (Rai et al., 2021). Once the agent completes the designated latency time period, it transitions to a condition of infectiousness. Infectiousness is considered within either an asymptomatic state, a presymptomatic state, or a symptomatic state. A hypothetical viral load is generated when the agent becomes infectious. The viral load can be described as the quantitative amount of the virus that slowly decreases according to the fixed viral reduction factor. The viral reduction factor is incorporated into the spatial simulation and differs according to the type of infectious state, i.e., an asymptomatic, presymptomatic or symptomatic state. The presymptomatic period is calculated within the spatial simulation model and, once complete, allows the agent to enter the clinical state of symptomatic. When in the clinical state of infectiousness, either asymptomatic, presymptomatic or symptomatic, an agent is able to infect other agents.

Infection can occur through two modes of viral transmission. Human-to-human transmission or through a viral load released into a building, representing fomite transmissions. Human transmissions occur through close contacts, such as fellow agents completing activities with an infectious agent.

The infectious period for an agent is dependent on an age-defined probability distribution, which is calculated using the built in Log-normal function of the GAMA Platform. Agents within an asymptomatic state will remain in this state until their individual infectious period is complete. Once the infectious period is completed and the viral load eradicated, the agent will transition from an infectious clinical state to the clinical state of recovered. Symptomatic agents, however, have a possibility of requiring hospitalization or intensive care (ICU). The possibility of requiring hospitalization or intensive care is determined by fixed parameters. The fixed parameters denote the proportion of agents within the specified age groups, that would require hospitalization or intensive care.

Once an agent enters into the clinical state of requiring hospitalization, it has the possibilities of recovering, being transferred to intensive care or dying. While in the clinical state of requiring intensive care, an agent has the possibilities of moving back to the clinical state of requiring hospitalization or dying. The transition from one clinical state to another, while within the clinical states of requiring hospitalization or intensive care, depends on the age of the individual agent and the appropriate epidemiological parameters. To be removed from hospital once recovered, the agent needs to obtain the applicable number of negative tests, which is an integrated function of the

COMOKIT model. Once an individual agent has recovered, it is identified as immune to the viral transmission of COVID-19 and a reinfection is not permitted for this study.

4.4. Functional Adaptations of COMOKIT

No public transport network is present within the spatial simulation tool and movement of the individual agents from one building to another is instantaneous. A public transportation system is developed by adapting the tool to include an additional action before the instantaneous change in location per individual agent. The additional action allows a portion of individual agents, those with an agenda, to instantaneously enter a transportation entity for a set time, before proceeding to the required activity. The autonomy of the agents allows for no daily use, singular or multiple daily use of the transportation system. The difference between transportation entities and the built environment entities, is the size of the transportation entity. The transportation entities are considerably smaller in comparison to the larger buildings, limiting the distance between the individual agents present within each minibus taxi or bus. When considering the built environment, buildings are large allowing individual agents to maintain a larger distance between themselves.

The transport network is implemented using this approach, to reduce the amount of computer processor capacity required. Sector A and Sector B consist of a large number of individual agents required to carry out autonomous agendas. The agendas require a large amount of computer processor capacity. This method used to implement the transport network allows for a more efficient simulation with regards to time and functionality.

The model is consequently adapted to favour human-to-human viral transmission through close contact of individual agents within the same building. This will allow a high probability of viral transmission within a radial distance of 1.5-meters from an infected agent. Viral transmission will therefore occur from an agent already infected with the virus and in an infectious state, to an agent that is not yet infected and in a susceptible state. This was a critical function to support and define the viral transmission dynamics within a public transport system. The initial simulation favoured human-to-human transmission within predetermined social groups of individual agents, with a declining risk of viral transmission to susceptible agents located within the same building. While this method of transmission is effective in areas that are typically dependent on private transportation, the simulation reduced the accuracy of spatial transmission within a public transport environment. This is verified by conducting several sensitivity analyses within the simulation and comparing the results between the areas relying on private transport and the areas relying on public transport. The sensitivity analyses focused on three situations of viral transmission, namely human-to-human transmission only, environmental transmission only, and both human-to-human and environmental transmission.

Since infection from COVID-19 differs greatly across individuals, typically limiting human health, many individuals cannot carry out daily agendas. The tool is further adapted to allow some portion of the infected and symptomatic individuals to remain within their place of residency until they are no longer symptomatic. This adaptation represents individuals requiring a recovery period in the form of a leave of absence. The leave of absence may be from their employment, and/or from alternative daily agendas, such as shopping or visiting friends. Once the individual agents are no longer in a symptomatic state, they will return to their predetermined agendas.

4.5. Scenario Implementation within COMOKIT

In order to identify the impacts of population density, public transport, and population age structure, in the spread of COVID-19, two different modes of viral transmission are executed within both Sector A and Sector B. The first scenario will be one of and undisrupted viral transmission. Each sector will be given the scenario of an undisrupted viral transmission of COVID-19. In this scenario the virus causing COVID-19 is transmitted with no mitigation strategies in place. Mitigation strategies including lockdown, where by schools and workplaces close, as well as the application of masks. This scenario allows the virus to be transmitted throughout the agents and spatial simulation without limitations. The second scenario implemented within each sector is one that restricts viral transmission during the spatial simulation. Within a restricted viral transmission scenario, mitigation strategies are implemented in an attempt to contain the virus and limit its transmission. Lockdown strategies are implemented, forcing the closure of schools and workplaces. Access to shopping centres is available, however, social visits are not permitted during the implementation of mitigation strategies. Lockdown strategies significantly hinders agent interaction and within the spatial simulation, thereby delaying viral transmission between the agents. The conceptual use of masks is used to limit viral transmission between the agents, as well as reduce the viral load transferred into buildings, preventing environmental infections occurring from contaminated objects.

4.5.1. Undisrupted viral transmission within COMOKIT

Each simulation executed by the spatial simulation model, COMOKIT, is governed by the strategies implemented. Within an undisrupted viral transmission, no strategies are applied. This describes a viral transmission that is not contained through mitigation attempts, and spreads between the agents and the environment without limitations. Table 4.5.1 describes the strategy factors used to define an undisrupted viral transmission within the spatial simulation. For this mode of viral transmission, COMOKIT is executed without the implementation of mitigation strategies such as lockdown and the application of masks. Agents continue with daily agendas and activities throughout the simulation. The agents are given access to all building types while social gatherings are permitted throughout the length of the simulation.

The spatial simulation begins with the introduction of random COVID-19 infection within an agent. The agents move through the simulation, performing their given activities per day. Agents execute their daily agendas depending on their individual age and the time and day of the week. The newly infected agent will continue to move through the sector performing its daily agenda until symptom onset. If the agent is asymptomatic, it will continue performing its daily agenda until the agent recovers from the illness. If the agent is symptomatic, however, it could either continue performing its designated daily agenda, or remain at home until it is no longer symptomatic. Depending on the agents age, it may require hospitalization or intensive care for medical assistance. Regardless of the type of symptoms onset, the agent is capable of infecting susceptible agents within a 1.5-meter proximity or may release a viral load into the buildings it associates with. Susceptible agents that enter the contaminated buildings, are at risk of COVID-19 infection. The agent either recovers from the viral infection or dies. If the agent recovers, it becomes immune to secondary infection; if the agent dies, it is removed from the simulation entirely.

Table 4.5.1: The strategy factors describing an undisrupted viral transmission, executed for Sector A and Sector B, within the spatial simulation model, COMOKIT.

Strategy Tolerance Factor	**Sector A**	**Sector B**
Essential Workers (%)	100	100
Mobility Tolerance (%)	100	100
Shopping Activity (%)	100	100
Transport Activity (%)	100	N/A
School Activity (%)	100	100
Non-essential Activities (%)	100	100
Masks Application (%)	0	0

The undisrupted viral transmission occurs for the entirety of the spatial simulation and is implemented for both Sector A and Sector B. The number of infections occurring per day and for each age group is extracted, as well as the number of infections that occurred within each building type. The extracted data will be analysed and compared using descriptive and exploratory data analysis.

4.5.2. Restricted viral transmission within COMOKIT

For the scenario where viral transmission is restricted, mitigation strategies are introduced. These strategies correlate to the mitigation policies implemented worldwide to delay the spread of Covid - 19. Lockdown policies that were implemented required individuals to remain within their residences for the duration of # months, with travel only permitted for essential purposes. This policy aimed to isolate the population and restrict exposure to the virus. Individuals that were able to, worked from their place of isolation, while those termed essential workers, were obligated to travel to work.

Different levels of lockdown were implemented, with severe lockdown policies requiring the closure of schools and many businesses. Retail businesses supplying essential items remained open, but limited the number of individuals within the buildings, increasing the distance between individuals. Individuals were required to wear masks covering oral and nasal regions to prevent viral transmission and object contamination from viral load release. COMOKIT contains numerous strategies that closely replicate these preceding mitigation policies for experimental studies.

Since different levels of lockdown were implemented throughout South Africa, the scenarios of restricted viral transmission will be focused on two different approaches, a severe mitigation strategy, and a lenient mitigation strategy. The two lockdown strategies are implemented within the spatial simulation, with the application of masks by agents.

Severe restriction of viral transmission within COMOKIT

Within both Sector A and Sector B, the severe lockdown strategy aims to be realistic in terms of agent mobility, whereby mobility during lockdown occurs but is significantly reduced in comparison to an undisrupted viral transmission. Table 4.5.2.1. describes the strategic factors used to implement the severe mitigation strategies within the spatial simulation, for Sector A and B.

Table 4.5.2.1: The strategy factors describing the severe mitigation strategies executed for Sector A and Sector B, within the spatial simulation model, COMOKIT.

Strategy Tolerance Factor	**Sector A**	**Sector B**
Essential Workers (%)	30	30
Mobility Tolerance (%)	30	30
Shopping Activity (%)	30	30
Transport Activity (%)	30	N/A
School Activity (%)	0	0
Non-essential Activities (%)	30	30
Masks Application (%)	80	80
Work From Home (%)	5	30

The lockdown strategy implemented for Sector A and Sector B within the spatial simulation, constrains the agents to their residential buildings, to isolate susceptible households from potentially infected households or agents. While individuals are within their residential buildings, however, isolation from family members does not occur within the spatial simulation. There is a high probability of infection within residential buildings, from an infected agent to a susceptible relative. A small portion of the population is permitted to return to work, representing essential workers, while school activities are not permitted. The strategy factor referring to essential workers, indicates the percentage of the population termed essential workers. A minimal tolerance of 10% is given to certain activities, such as shopping and travelling, due to the requirement of essential items and the support of public transport in Sector A. The mobility tolerance defines 10% of the population permitted to travel. No social visits are permissible within the spatial simulation, while public parks and additional areas, such as public pools or sporting fields, and additional non-essential building-types, are closed for use. The application of masks is required by individual agents, however, only 80% of the population was given the requirement of mask use to compensate for the possible incorrect techniques used for the application of masks (Robinson et al., 2022).

Moderate restriction of viral transmission within COMOKIT

A moderate mitigation strategy allows for more agent mobility throughout the spatial simulation. A larger portion of the population is permitted to return to work, while additional workers remain home. This is achieved by increasing the number of essential workers to 70% in Sector A and 40% in Sector B. The difference in the proportion of essential workers and mobility tolerance is used to highlight the difference in socio-economic factors between Sector A and Sector B. Sector B describes a larger proportion of the population with the advantage of working from home, while Sector A consists largely of unskilled, manual workers that are required onsite to earn an income. Unemployment is higher in Sector A, leading to a high mobility of individuals seeking employment.

Table 4.5.2.2: The strategy factors describing the moderate mitigation strategies executed for Sector A and Sector B, within the spatial simulation model, COMOKIT.

Strategy Tolerance Factor	**Sector A**	**Sector B**
Essential Workers (%)	70	70
Mobility Tolerance (%)	70	70
Shopping Activity (%)	70	70
Transport Activity (%)	70	N/A
School Activity (%)	100	100
Non-essential Activities (%)	70	70
Masks Application (%)	80	80
Work From Home (%)	5	30

Essential activities, such as shopping and transportation, are permitted within the moderate mitigation strategy, as well as non-essential activities, for instance social gatherings. Non-essential building-types, such as restaurants and public areas are permitted with the proportion of agents executing daily agendas, associated to the mobility tolerance of the moderate mitigation strategy. Agents are permitted to return to school. The moderate mitigation strategy describes a proportion of younger agents returning to school as this is correlated to the mobility tolerance factor, indicating a proportion of younger agents that remain home. The application of masks remains at 80% of the population as the requirement of masks remained well over the implementation period of the different lockdown policies within South Africa.

4.5.3. Technical properties of COMOKIT

The spatial simulation continues until it reaches a specified number of cycles. Each spatial simulation cycle represents an hour within the simulation. Each simulation executed for Sector A and Sector B takes approximately 1 hour to 2 hours depending on the scenario of viral transmission implemented within the spatial simulation. The simulations for an undisrupted viral transmission are run for approximately 3000 cycles, which is equivalent to four months within the model. The simulations for a moderately restricted viral transmission are simulated for approximately 4000 cycles, equivalent to 6 months. The simulations for a severely restricted viral transmission are simulated for roughly 7200 cycles, which is equivalent to 10 months. Five simulations were run for each sector, for each relevant scenario. The complete number of simulations executed for the purpose of this study is thirty-five.

4.6. Experimental Approach

The full number of days required for the eradication of the COVID-19 virus from the spatial simulation, as well as infection growth over time, will be established for each sector and scenario, and qualitatively analysed. The results of the undisrupted viral transmission scenario and restricted viral transmission scenario for Sector A and Sector B will be compared.

Infection growth over time will be compared between the two sectors, in relation to the two main variables of each area, specifically population density and the implementation of public transport. While Sector A and Sector B have similar populations, each sector is significantly different in spatial area, providing the variation in population densities. Sector A describes a large population within a smaller spatial area. Additionally, the buildings within Sector A are considerably smaller in spatial area. Both Sector A and Sector B are comprised of a similar number of buildings per building-type to ensure equality across the sectors. The only disparities between Sector A and Sector B, are the spatial area, thus, population density, and the use of public transport. It is expected that the smaller buildings of Sector A would reduce the spatial area between agents and possibly increase the risk of exposure to the virus. With the increased risk, the number of agents being infected within a given day may increase. A larger number of infections per day, together with a fewer number of days required for eradication of the virus, can infer an impact of either population density or public transport. To isolate population density only, Sector A will be simulated within an undisrupted viral transmission and compared to Sector B. Comparisons will be made for the undisrupted viral transmission and the restricted viral transmission scenarios. It is expected that population density will increase the rate of viral transmission during undisrupted viral transmission, but transmission will not be affected by population density during severe and moderate mitigation strategies.

For each scenario and sector, the impact of the population age structure will be examined and compared. The impact of the population age structure on the spread of COVID-19 will be determined by identifying which buildings encourage both human-to-human and environmental viral transmission more efficiently. Once the buildings of interest are identified, a correlation may be made between the buildings and population age structure. Comparisons will be made between the undisrupted viral transmission and the restricted viral transmission scenarios and the impact population age structure for each scenario. It is expected that different age groups will encourage viral spread for each scenario. Within an undisrupted viral spread, it is expected that school-type buildings will promote viral transmission more efficiently, meaning agents categorized in the younger age groups have more of an impact during an undisrupted viral transmission. Since no access is granted to school-type buildings during severely restricted viral transmission scenarios, it is expected that work-type buildings will encourage viral transmission more efficiently. In this scenario, agents categorized within the economically active portion of the population, produce more of an impact within a severely restricted viral transmission. Within a moderately restricted viral transmission scenario, it is expected that both school-type buildings and work-type buildings will have an equalised impact of viral transmission, meaning viral transmission is not impacted by any specific age group.

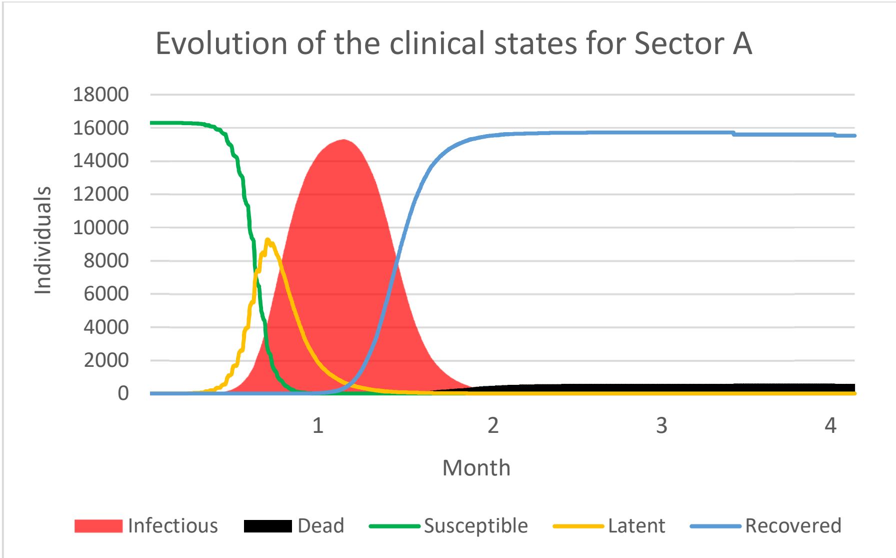
The impact of public transport on the transmission of the COVID-19 virus can be determined by the number of infections occurring within the public transport entities in comparison to the buildings of the built environment found within Sector A. It is expected that significantly more infections will occur within public transport entities due to the minimal spatial area attributed by the bus and minibus taxi entities, and the prevalent form of transport within Sector A. More infections are expected to occur within public transport entities during undisrupted viral transmission when compared to restricted viral transmission, since the number agents traveling is reduced during restricted viral transmission.

5. Results

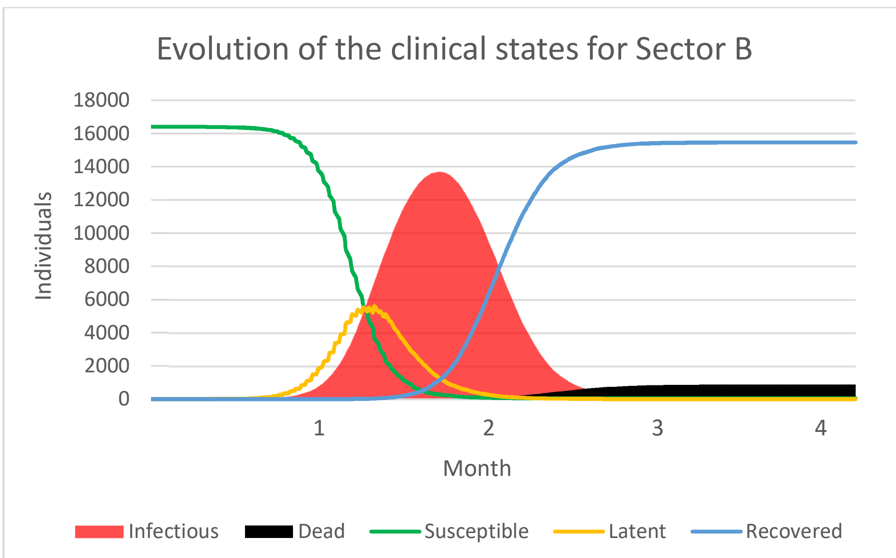
The results are displayed by epidemic curves, which describe the evolution of the clinical states, or the incident case number comparisons. The epidemic curves display single peak curves due to the omission of viral reinfection by agents. This allowed for short term monitoring of viral transmission throughout Sector A and Sector B. By omitting reinfection of agents, a timeline could be established for each sector, attributing to the introduction and complete suppression of COVID-19 per sector, and the time required per sector.

The speed of viral transmission is determined by the number of days required to suppress the virus within the simulation environment. The simulation starts with the infection of two randomly selected agents within either Sector A or Sector B. Introduction to the virus therefore occurs at the same time for both Sector A and Sector B. The simulation is considered complete once the agents have recovered from viral infection, been removed from the simulation environment due to death from viral infection, or the virus is no longer considered active within the spatial simulation environment. The virus is considered inactive once no further infections can occur.

The epidemic curves defined by Figure 5.1(a) and Figure 5.1(b), describe the evolution of the clinical states for Sector A and Sector B respectively, within an undisrupted transmission of COVID-19. A difference between the two epidemic curves is visible by the steepness of the susceptible clinical state of Sector A, described by Figure 5.1(a). The state curve decreases rapidly within the first month of the conceptual introduction of COVID-19 into the community. The latency state curve peaks within the first month of infection within the community. In comparison, the susceptibility of Sector B, illustrated by Figure 5.1(b), begins to decrease approximately one month from conceptual introduction of the virus, while latency peaks after the first month. Most of the population had recovered within two months of viral inception into Sector A, while most of the population of Sector B recovered after 2.5 months. The number of deaths that occurred were higher within Sector B than the number of deaths that occurred within Sector A.



(a)



(b)

Figure 5.1: Evolution of the clinical states for (a) Sector A and (b) Sector B, within a spatial simulation environment given an undisrupted viral transmission of COVID-19.

Figure 5.2 compares the number of incident case numbers for Sector A and Sector B within an undisrupted transmission of COVID-19 and is obtained from the infectious state curves per sector. The incident curve for Sector A describes a more rapid viral transmission than that of Sector B, which is evident by the steep incline of incident cases before the first month of conceptual introduction of the virus into the simulation environment. At the end of the first month, the number of incident cases reached approximately 14,000 within Sector A. In comparison to Sector A, the incident curve of Sector B describes a more gradual incline of incident cases, indicating that incident cases began to increase more quickly after the first month of conceptual viral introduction. At the end of month one, the number of incident cases reached approximately 3,000, describing a far slower transmission of COVID-19 through the Sector B than that of Sector A. Both incident case curves describe and undisrupted viral transmission within each sector. As a result, the number of incident cases for each sector, peak within the first two months of conceptual viral introduction, indicating a rapid viral transmission within both Sector A and Sector B.

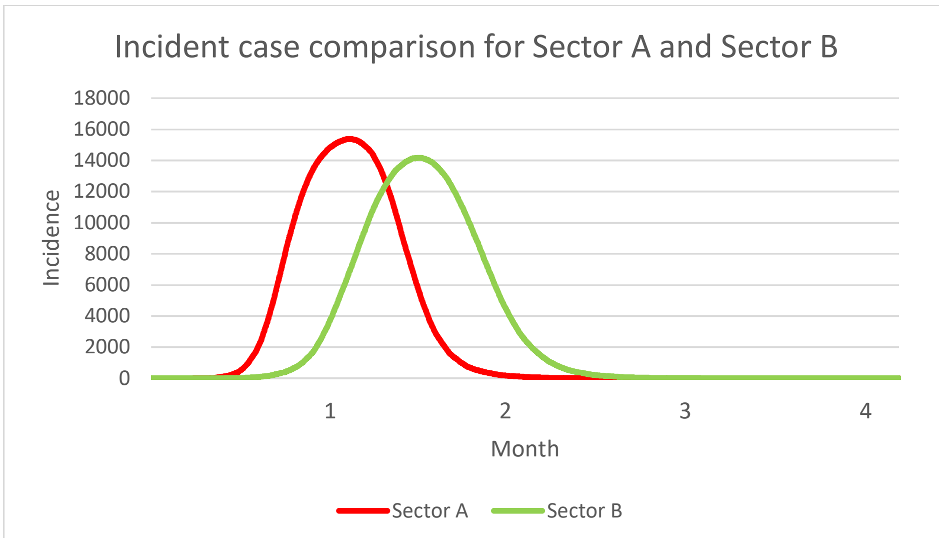


Figure 5.2: A comparison of the average incident case for Sector A, with public transport, and Sector B given an undisrupted viral transmission of COVID-19.

Figure 5.3 describes an incident case comparison of Sector A with and without the implementation of a public transport network, with the incident cases of Sector B given an undisrupted viral transmission. Sector A simulated without the implementation of a public transport network, removes the public transport variable, leaving population density as the only considerable difference between Sector A and Sector B. As illustrated by Figure 5.3, both public transport and population density impact the transmission of COVID-19, as evident by the earlier start of case incident curves for Sector A with and without public transport. The incident curve for Sector A with public transport resulted in the fastest speed of viral transmission, while Sector B, with a low population density and lack of public transport network, demonstrated the slowest speed of viral transmission.

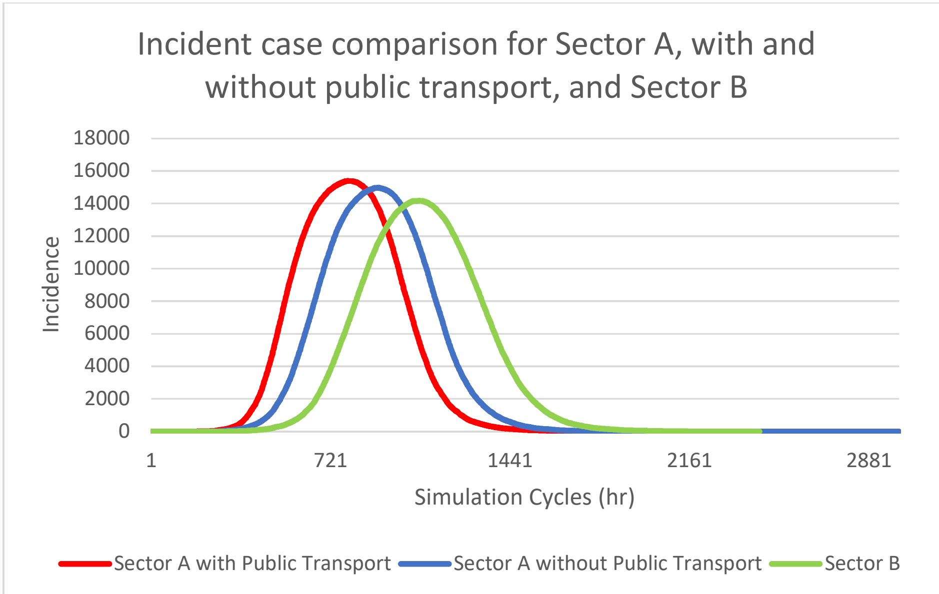
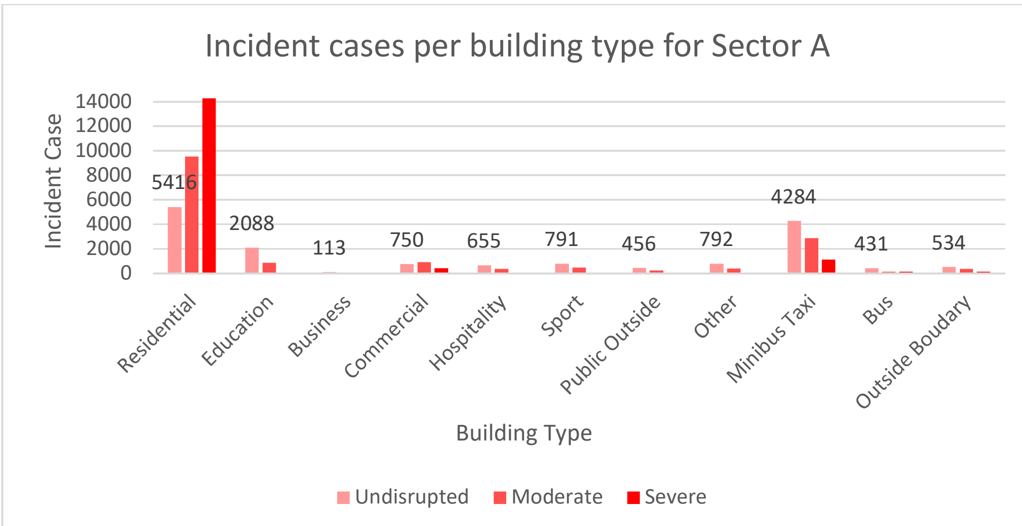
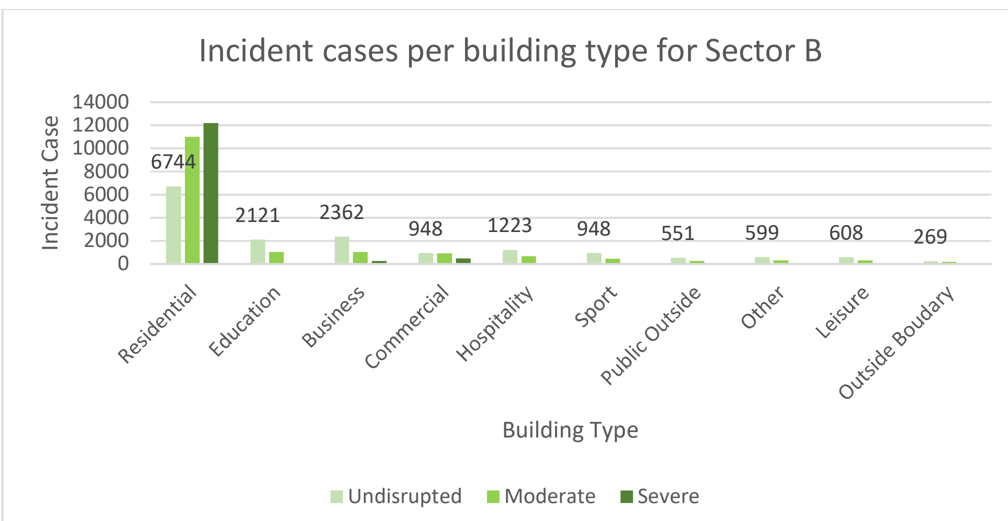


Figure 5.3: A comparison of the average incident case for Sector A, with and without the implementation of public transport, and Sector B given an undisrupted viral transmission of COVID-19.

Viral exposure occurs within or from each building denoted by its land-use type. Exposure to the virus and the resulting Infection may result from either human-to-human viral transmission, or through environmental viral transmission. Figure 5.4(a) and (b) display the distribution of incident cases created from or within the defined buildings for Sector A and Sector B respectively. The incident case distribution per building is given for an undisrupted viral transmission, a moderate restriction of viral transmission, and a severe restriction of viral transmission that was implemented within the spatial simulation environment for both Sector A and Sector B. Figure 5.4(a) describes the incident case distributions per building type for Sector A. As observed, most infections resulted within and from residential building types and the public transport entities, minibus taxis. The number of infections occuring from or within minibus taxis was reduced with the implementation of mitigation strategies to restrict viral transmission. A moderately restricted viral transmission reduced the number of infections resulting from or within minibus taxis by 33%, while a severely restricted viral transmission reduced infections by 74%. For both Sector A and Sector B, described by Figure 5.4(b), the number of infections resulting within and from each specified building decreases with the severity of the restriction strategies implemented. However, infections occurring within residential type buildings increased with the severity of restriction strategies implemented. The number of incident cases resulting within or from business type buildings of Sector A, is significantly less than those resulting within or from the business type buildings of Sector B. Schools are an evident contribution to the number of incident cases within both sectors. The closure of schools during a severe restrictions of viral transmission, contributed to the increase in residential related incident cases.



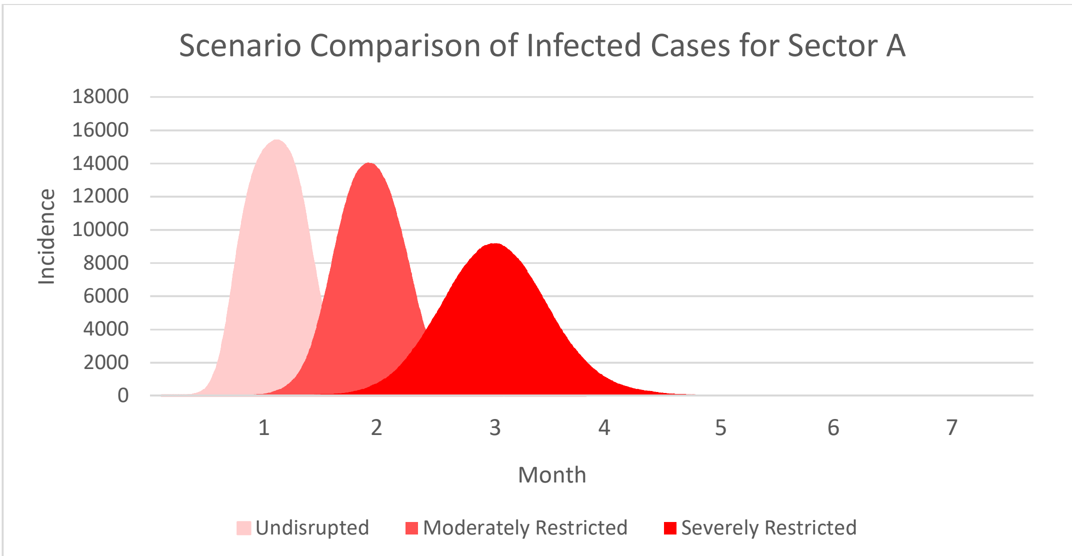
(a)



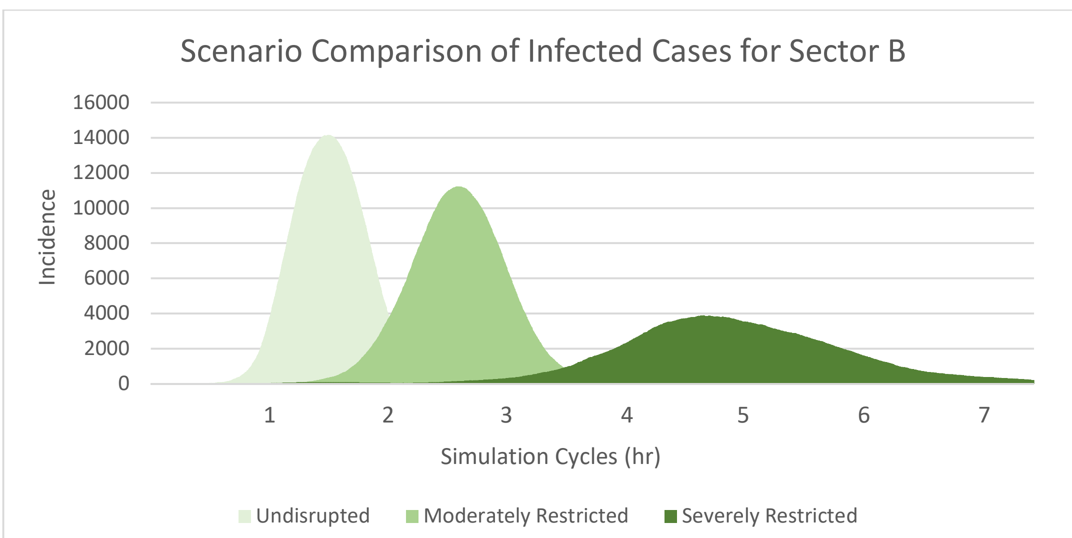
(b)

Figure 5.4: The number of incident cases created within or from the associated buildings within (a) Sector A, with public transport, and (b) Sector B, given an undisrupted, moderately restricted, and severely restricted viral transmission of COVID-19.

The mitigation strategies that were implemented within Sector A and Sector B, were implemented in an attempt to reduce the speed of viral transmission throughout the spatial simulation environments of COMOKIT. A reduced speed is shown by a flatter epidemic curve defined for the number of incident cases. A time delay in viral transmission is also expected, due to the reduced number of daily contacts. A time delay is evident by measuring the time from conceptual introduction of the virus, COVID-19, into the spatial simulation, to the time of noticeable increase of case incidents represented by the epidemic incident case curve.



(a)



(b)

Figure 5.5: A comparison of the average incident cases for (a) Sector A, with public transport, and (b) Sector B given an undisrupted, moderately restricted, and severely restricted viral transmission of COVID-19.

Figure 5.5(a) and (b) describe the comparison of case incidents within each scenario of COVID-19 transmission, for both (a) Sector A and (b) Sector B. The scenarios define an undisrupted, moderately restricted, and severely restricted viral transmission within the spatial simulation environments. Figure 5.5(a) and (b) describe three single-peaked case incident curves, each curve describing the type of viral transmission implemented. With an increase in the severity of restriction strategies implemented, a time delay in viral transmission, as well as curve flattening, is evident for both Sector A and Sector B. A significantly greater time delay and curve flattening is evident in Sector A, described by Figure 5.5(b), in comparison to Sector A, described by Figure 5.5(a). Table 5.1 defines the number of months required to eradicate viral transmission within Sector A and Sector B, per scenario.

Table 5.1: The number of months required for Sector A, with public transport, and Sector B to eradicate viral transmission, within an undisrupted, moderately restricted, and severely restricted viral transmission of COVID-19.

	Undisrupted	**Moderate Restricted**	**Severe Restricted**
Sector A	3.5	4.5	6
Sector B	4.5	5.5	10

Within Sector A, a moderately restricted viral transmission delays viral infection by one month, while a severely restricted viral transmission delays viral transmission by approximately 2.5 months. Within Sector B, viral transmission is delayed by one month with the implementation of a moderately restricted viral transmission, and 5.5 months with the implementation of a severely restricted viral transmission.

Figure 5.6 illustrates the percentage of the population removed from the spatial simulation scenarios, due to COVID-19 related deaths. As illustrated, COVID-19 related mortality decreases for both Sector A and Sector B with the implementation of moderately and severely restricted viral transmission. Sector B demonstrated a larger decrease in population mortality, with a reduction of 7% of deaths when viral transmission is moderately restricted and a reduction of 23% of deaths when viral transmission is severely restricted. In comparison, Sector A demonstrated less decrease in population mortality with a 5% reduction in deaths when a moderately restricted viral transmission was implemented, and a 10% reduction in deaths when viral transmission was severely restricted.

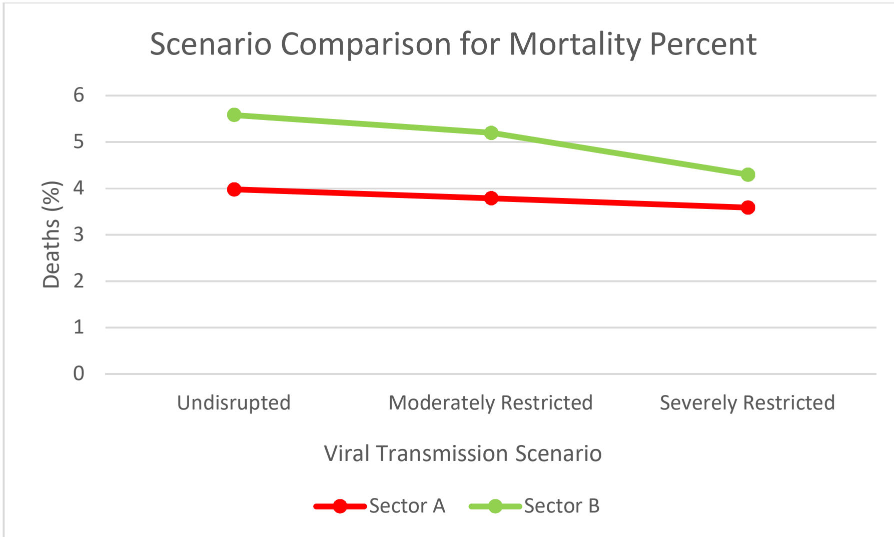


Figure 5.6: A comparison of the percent mortality for Sector A, with public transport, and Sector B given an undisrupted, moderately restricted, and severely restricted viral transmission of COVID-19.

As evident by the compiled results, differences exist between the two socio-economically diverse areas, Sector A and Sector B, related to the impact of socio-economic factors on an undisrupted transmission and restricted transmission of COVID-19.

6. Discussion

Sector A is considered a low-income area as it is described by a high population density and high unemployment. Sector A relies predominantly on public transport and consists mostly of individuals below the age of thirty years. Sector B, a high-income area is described with a low population density, and low unemployment. Sector B relies primarily on private transport, the population of which consists of fewer individuals below the age of thirty, and more individuals above the age of sixty, in comparison to demographics of Sector A (Open Africa, 2017).

Due to the high unemployment of Sector A, the number of incident cases resulting within or from business type buildings during an undisrupted transmission of COVID-19, was significantly lower than that of the business type buildings within Sector B, which yielded approximately 2,360 incident cases. Minibus taxis yielded over 4,000 incident cases, which can be associated to the limitation of space within minibus taxis. Within South Africa, the minibus taxis are an integral part of public transport sector and are in high demand within low-income areas (Fobosi, 2013). According to the Comprehensive Integrated Transport Plan (SSI Engineers and Environmental Consultants, 2011), approximately 372,866 personal journeys are made using minibus taxis on a daily basis within the city of Port Elizabeth. The small spatial area and confinement within minibus taxis does not allow for social distancing measures to be put in place. The application of masks may reduce the number of infections, however, due to close confinement within the minibus taxis, lack of social distancing and the incorrect application of masks, masks cannot completely remove infections occuring from or within minibus taxis. The minibus taxi industry relies economically on the number of passengers transported and the number of trips made per day, which often encourages over population within minibus taxis. All three scenarios of viral transmission demonstrated a larger number of infections occuring from or within minibus taxis when compared to the number of infections occuring from or within the additional non-residential type buildings. The number of incident cases occurring from or within busses is siginificantly lower to that of minibus taxis. Busses are larger than minibus taxis, allowing for social distancing between passengers. Busses are slower and follow a strict schedule in comparison to minibus taxis that are numerous and operate more frequently throughout the day. The number of Infections occuring from or within the non-residential buildings of Sector B are evidently higher than the quantitative results of the buildings within Sector A. This is due to the lack of public transport within Sector B, which relies primarily on private transport. The additional associations made within public transport are absent from Sector B reducing the risk of infection associated with public transport by 100%. This implies that public transport, with emphasis on minibus taxis, largely impacts the transmission of COVID-19 within Port Elizabeth, South Africa, due to the confinement of passengers within the small spatial areas, as well as the dependence of minibus taxis by the portion of the population that cannot afford private transport.

Incident cases associated with the residential buildings of both sectors, during the different scenarios of COVID-19 transmission, were significantly higher when compared with incident cases related to the non-residntial type buildings. Considering social interaction between family members and friends, and social interactions within non-residential buildings, the high quantitative results of residential buildings is justified. Within non-residnetial buildings, close proximity between individuals is not often reached. If space relating to building area is available, individuals not within a social group will reduce proximity. Whereas individuals within a social group, such as family members or friends, will establish proximity, thereby increasing the risk of viral infection. Individuals experience longer time periods within residential buildings, further increasing the risk of infection between family members. The risk of infection is thus highest within residential buildings. Since the number of infections occurring within or from residential buildings surpassed the number of infections occurring from or within schools, it was found that the impact of population age structure on the transmission of COVID-19, was less significant than population density and the use of public transport.

Incident cases associated with the residential buildings during an undisrupted and moderately restricted transmission of COVID-19, were more apparent within Sector B. This can be attributed to the influence of population density and public transport within Sector A. Residentially produced incident cases increase significantly within Sector A during severly restricted viral transmission, when the use of public transport is significantly reduced. The spatial area of the residential buildings within Sector A are significantly smaller than those of Sector B. Overcrowding of residential buildings within Sector A is apparent by the parameters used to synthesize the poulation. A high population density within the political ward for Sector A, is attributed by the small residential buildings and large number of crowded households. With the evident crowding and small spatial areas of residential buildings, the risk of infection within residential buildings of Sector A, is somewhat higher than the risk of infection within the residential buildings of Sector B.

Within Sector B, infection and the resulting incident cases were reduced. The severe mitigation strategies implemented within the sector, managed to eradicate the virus before the entirety of the population was infected. These mitigation strategies were implemented for approximately ten months resulting in the early eradication of the virus within Sector B. Mitigation strategies implemented for this length of time would have substantially negative consequences on the economy and is therefore not feasible. For the purpose of the study, however, the mitigation strategies were implemented for as long as the conceptual virus was active within each sector for the purpose of comparison between the sectors and related scenarios of transmission.

The restriction strategies implemented reduced the number of deaths occuring within each sector. Sector B showed the greatest reduction in deaths in comparison to the number reduced deaths of Sector A. Early eradication of the virus within Sector B contributed to the larger number of deaths avoided.

An undisrupted transmission of COVID-19 displayed a faster spread throughout both Sector A and Sector B, Sector A showing the fastest transmission of the virus. A moderately restricted transmission of the virus within each sector, demonstrated some delay of the virus and some flattening of the epidemic incident case curve, a time delay and curve flattening was more evident within Sector B than Sector A. A severely restricted viral transmission within each sector showed a larger time delay and epidemic curve flattening, with a more apparent display of transmission delay and curve flattening for Sector B. The difference in results between Sector A and Sector B have been proven by the difference in population density and the use of public transport.

7. Conclusion

Mitigation strategies were implemented globally, in an attempt to delay viral transmission to provide medical practitioners and scientists with time. Time to conduct enough research, to begin development towards a vaccine, to prepare countries with adequate personal protective equipment (PPEs), to prepare hospitals for a possible influx of patients, which was required to reduce the number of COVID-19 related deaths.

The use of spatial simulations within epidemiology is essential in examining and predicting viral transmission infection dynamics. For this study, the impact of socio-economics were examined and comparison between two socio-economically diverse areas within Southern Africa were made. Different scenarios of transmission were implemented within a spatial simulation environment, a scenario in which viral transmission is undisrupted, a scenario in which viral transmission is moderately restricted, and a scenario in which viral transmission is severely restricted. These scenarios were implemented within two socio-economically diverse areas (Sector A and Sector B) to identify the impact of mitigation methods and the impact of population density, the use of public transport, and the influence of population age structure, on the transmission of COVID-19.

Although the implementation of mitigation strategies delayed the transmission of COVID-19 and displayed curve flattening, a large difference is evident between the epidemic curves of Sector A and Sector B. Viral transmission within Sector B could be reduced more effectively with the use of mitigation strategies in comparison to Sector A. This is attributed to the high population density and use of public transport within Sector A in comparison to the low population density and use of private transport within Sector B. The impact of the population age structure was found to have a lesser impact on the transmission of COVID-19, as infections were largely encouraged within residential buildings.

Population density and public transport thus demonstrated to have a considerable impact on the transmission of COVID-19. High population density and the use of public transport increase the speed of viral transmission and reduces the ability to manage viral transmission and the resulting COVID-19 related deaths. Population age structure was found to have a lesser impact on the transmission of COVID-19, as infections were largely encouraged within residential buildings. The findings of this research may be relevant for alternative infectious deseases that require the close proximity of indiviuals for transmission.

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Appendix A: Population parameters for Sector A and Sector B

Sector A: Population Parameters	
Parameter	**Value**
proba_active_family	0.9
number_children_mean	3.8
number_children_std	3.5
number_children_max	5.5
proba_grandfather	0.23
proba_grandmother	0.26
retirement_age	65
max_age	85
nb_friends_mean	5
nb_friends_std	3
nb_classmates_mean	6
nb_classmates_std	5
nb_work_colleagues_mean	5
nb_work_colleagues_std	3
proba_unemployed_M	0.8
proba_unemployed_F	0.7
work_at_home	0.05

Sector B: Population Parameters	
Parameter	**Value**
proba_active_family	0.7
number_children_mean	2.4
number_children_std	2.6
number_children_max	3.0
proba_grandfather	0.44
proba_grandmother	0.46
retirement_age	65
max_age	85
nb_friends_mean	5.0
nb_friends_std	3.0
nb_classmates_mean	6.0
nb_classmates_std	5.0
nb_work_colleagues_mean	5.0
nb_work_colleagues_std	3.0
proba_unemployed_M	0.12
proba_unemployed_F	0.1
work_at_home	0.1

Appendix B: Agenda parameters for Sector A within an undisrupted transmission of COVID-19

Agenda Parameter	Value	
non_working_days	5	7
work_hours_begin_min	7	
work_hours_begin_max	10	
work_hours_end_min	15	
work_hours_end_max	18	
school_hours_begin_min	7	
school_hours_begin_max	9	
travel_hours_begin	4	
travel_hours_end	23	
school_hours_end_min	14	
school_hours_end_max	17	
first_act_hour_non_working_min	7	
first_act_hour_non_working_max	11	
lunch_hours_min	12	
lunch_hours_max	14	
max_duration_lunch	1	
max_duration_default	2	
min_age_for_evening_act	13	
nb_activity_fellows_mean	3	
nb_activity_fellows_std	2	
max_num_activity_for_non_working_day	5	
max_num_activity_for_old_people	4	
max_num_activity_for_unemployed	4	
proba_activity_evening	0.5	
proba_lunch_outside_workplace	0.1	
proba_lunch_at_home	0.5	
proba_go_outside	0.5	
proba_work_outside	0.7	
building_neighbors_dist	50	

Appendix C: Agenda parameters for Sector B within an undisrupted transmission of COVID-19

Agenda Parameter	Value	
non_working_days	5	7
work_hours_begin_min	7	
work_hours_begin_max	10	
work_hours_end_min	15	
work_hours_end_max	18	
school_hours_begin_min	7	
school_hours_begin_max	9	
travel_hours_begin	4	
travel_hours_end	23	
school_hours_end_min	14	
school_hours_end_max	17	
first_act_hour_non_working_min	7	
first_act_hour_non_working_max	11	
lunch_hours_min	12	
lunch_hours_max	14	
max_duration_lunch	1	
max_duration_default	2	
min_age_for_evening_act	13	
nb_activity_fellows_mean	3	
nb_activity_fellows_std	2	
max_num_activity_for_non_working_day	3	
max_num_activity_for_old_people	3	
max_num_activity_for_unemployed	3	
proba_activity_evening	0.5	
proba_lunch_outside_workplace	0.1	
proba_lunch_at_home	0.5	
proba_go_outside	0.5	
proba_work_outside	0.7	
building_neighbors_dist	50	

Appendix D: Activity- and building-type weights for Sector A and B within an undisrupted transmission of COVID-19

Activity Weights										
Age min	Age max	sex	visiting neighbor	visiting friend	eating	shopping	leisure	outside activity	sport	other activity
0	10	0	0.5	1.0	0.5	0.5	1.0	0.8	0.8	0.1
0	10	1	0.5	1.0	0.5	0.3	1.0	1.5	2.0	0.1
11	18	0	0.5	2.0	0.8	1.5	1.5	0.8	0.8	0.2
11	18	1	0.5	2.0	0.8	1.0	1.5	2.0	1.5	0.2
19	60	0	1.0	1.5	1.0	2.0	1.0	1.0	1.5	2.0
19	60	1	1.0	1.5	1.0	1.5	1.0	1.8	1.8	2.0
61	120	0	1.0	1.2	0.7	1.0	0.5	1.0	1.0	1.5
61	120	1	1.0	1.2	0.7	1.5	0.5	1.0	1.0	1.5

Building Type Weights								
Age min	Age max	sex	open space	park	community centre	church	minibus taxi	bus
0	10	0	1.0	1.0	0.5	0.5	1.0	1.2
0	10	1	1.0	1.0	0.5	0.5	1.0	1.2
11	18	0	2.0	2.0	1.0	0.7	2.0	1.8
11	18	1	2.0	2.0	1.0	0.7	2.0	1.8
19	60	0	0.5	1.0	1.5	1.0	2.0	1.8
19	60	1	0.5	1.0	1.5	1.0	2.0	1.8
61	120	0	0.3	0.8	1.8	1.5	1.0	0.8
61	120	1	0.3	0.8	1.8	1.5	1.0	0.8

Appendix E: Epidemiology parameters for Sector A and Sector B

Parameter	Age	Detail	Parameter_1	Parameter_2
Transmission_human		Fixed	TRUE	
Transmission_building		Fixed	TRUE	
Successful_contact_rate_human		Fixed	0.0340142	
Successful_contact_rate_building		Fixed	0.017	
Factor_asymptomatic		Fixed	0.45	
Proportion_asymptomatic		Fixed	0.28	
Basic_viral_release		Fixed	0.05	
Basic_viral_decrease		Fixed	0.1	
Probability_true_positive	0	Fixed	1	
Probability_true_negative	0	Fixed	0.91	
Proportion_wearing_mask	0	Fixed	0	
Factor_wearing_mask	0	Fixed	1	
Incubation_period_symptomatic	0	Lognormal	1.57	0.65
Incubation_period_asymptomatic	0	Lognormal	1.57	0.65
Serial_interval	0	Normal	3.96	4.75
Proportion_hospitalisation	0	Fixed	0.025	
Proportion_hospitalisation	20	Fixed	0.208	
Proportion_hospitalisation	45	Fixed	0.283	
Proportion_hospitalisation	55	Fixed	0.301	
Proportion_hospitalisation	65	Fixed	0.435	
Proportion_hospitalisation	75	Fixed	0.587	
Proportion_hospitalisation	85	Fixed	0.703	
Proportion_icu	0	Fixed	0	
Proportion_icu	20	Fixed	0.2019	
Proportion_icu	45	Fixed	0.3675	
Proportion_icu	55	Fixed	0.3721	
Proportion_icu	65	Fixed	0.4322	
Proportion_icu	75	Fixed	0.5281	
Proportion_icu	85	Fixed	0.4125	
Proportion_death_symptomatic	0	Fixed	0	
Proportion_death_symptomatic	20	Fixed	0.0476	
Proportion_death_symptomatic	45	Fixed	0.0769	
Proportion_death_symptomatic	55	Fixed	0.2321	
Proportion_death_symptomatic	65	Fixed	0.2606	
Proportion_death_symptomatic	75	Fixed	0.3387	
Proportion_death_symptomatic	85	Fixed	0.9414	
Infectious_period_symptomatic	0	Lognormal	2.8622	0.0685
Infectious_period_symptomatic	10	Lognormal	2.949688	0.094
Infectious_period_symptomatic	20	Lognormal	2.95491	0.047
Infectious_period_symptomatic	30	Lognormal	2.95491	0.033
Infectious_period_symptomatic	40	Lognormal	3.072693	0.04
Infectious_period_symptomatic	50	Lognormal	3.109061	0.037
Infectious_period_symptomatic	60	Lognormal	3.131137	0.039
Infectious_period_symptomatic	70	Lognormal	3.113515	0.08
Infectious_period_asymptomatic	0	Lognormal	2.8622	0.0685