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Agent-Based Modeling of COVID-19 Transmission: A Case Study of Housing Densities in Sankalitnagar, Ahmedabad

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Abstract: The differential transmission of COVID-19 depending on the socio-economic status of a neighborhood is well established. For example, several studies have shown that COVID-19 transmission was higher in poorer and denser neighborhoods than in wealthier ones. However, what is less well known is how this varied rate of transmission interacted with established health measures, i.e., face masks and lockdowns, in the context of developing countries to reduce pandemic cases and hence resulted in fewer deaths. This study uses an Agent-Based Model (ABM) simulation to examine the context and impacts of COVID-19 mitigation efforts (i.e., lockdowns combined with masks) on the transmission of COVID-19 across a single neighborhood in Ahmedabad, a city in the state of Gujarat, India. The model is parameterized using real-world population data, which allows us to simulate the spread of COVID-19 to find conditions that most closely match the realities of COVID-19 in the spring of 2020. Consequently, the simulation can be used to understand the impact of nation-wide lockdown on the spread of COVID cases across Ahmedabad as a function of housing density. Thus, invaluable insight into the effectiveness of a lockdown as a mitigation measure can be derived. Further information about how the effectiveness of the lockdown varied by neighborhood, as well as other factors that impacted it, can be ascertained.

Keywords: agent-based models; COVID-19; housing density

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1. Introduction

Spatially explicit Agent-Based Models (ABMs) are particularly useful for studying communicable diseases whose propagation is affected by the environment, such as sanitation and housing conditions [1]. While there exist other useful methods, such as expanded compartment models based on the well-regarded Susceptible–Infectious–Recovered (SIR) model [2–4], as well as meta-population models, the ABM approach was selected here as it (a) allowed for free mixing of individuals (as opposed to individuals allocated to specific spatially allocated grids) and (b) provided a mechanism for varying rules governing movement according to the underlying environment [5]. Moreover, ABMs are well placed to simulate the transmission of diseases as a complex process [6–8], as it is affected by factors such as heterogeneous interactions facilitated by network connectivity (both social and place-based) [9,10]. Such models can be further extended to specific geographic locales. For example, Ref. [11] simulated the propagation of a communicable disease through an urban milieu. This model incorporated the spatio-temporal dynamics of the urban environment, primarily focusing on exchanges between agents during commute time spent on a transportation network, or other possible interactions in specific locations such as workplaces, educational institutions (i.e., schools and universities), and shopping malls. Other ABMs, including stochastic ones [12], have been developed specifically for

COVID-19. Among the ones that considered environmental factors, Ref. [13] looked at spatially explicit factors that could govern spread, including GDP per capita, percentage of older adults in the province, population density, and the presence of mass transit systems. While Ref. [14] focused on the contributions of daily activities at an individual's workplace, Ref. [15] extended the models to look at how interzonal mobility restrictions would affect COVID-19 transmissions between groups.

In parallel, there has been extensive research on how specifically built environments facilitate the spread of COVID-19 [16]. Ref. [17] identified the risk of specific environments increasing the transmissibility of the virus. Specifically, they noted that the US prison system, worker dormitories in Singapore, and informal urban settlements would result in higher rates of transmission. Specific to India, Ref. [18] showed the variations in both infections and death rates when related to population densities of districts in four states, whereas Ref. [19] studied the risk of COVID-19 infection as a function of both proximity to hotspots as well as the socioeconomic and biophysical structure of communities in the city of Jaipur, Rajasthan state. Scholars have also noted that the mobility of individuals during COVID-19 was highly dependent on social class, with those from weaker socio-economic classes (e.g., migrants and minorities in Spain) mainly filling low-wage occupations that required travel to a workplace and could not be performed remotely [20].

Extending these studies to Agent-Based Models (ABMs), several simulations have been developed specifically to look at COVID-19 transmission between human populations [21–26]. One [27] specifically simulated how various social measures, i.e., reductions in mobility and social isolation, led to a reduction in cases. Here, we extend the work done to date by combining the role of specific built environments and neighborhoods (particularly the intermixing of formal and informal settlements) and mobility restrictions based on social class with Agent-Based Models (ABMs) to look at the spatio-temporal spread of COVID-19 in the context of a developing country.

Specifically, we ask the following question using an ABM: How did the measures to reduce the spread of COVID (i.e., mask-wearing and lockdowns) in the initial phases vary its rates of spread in one neighborhood (i.e., Sankalitnagar) in the city of Ahmedabad, India? Further, we also try to simulate via the ABM the differential rates of COVID infections as a function of its housing density (i.e., divided based on low- and high-density housing). The overall goal, therefore, was to understand how the conditions of lockdown and prescription of mask-wearing that were in place at the time may have differentially affected rates of spread, in addition to the variations caused by different housing densities. We chose Sankalitnagar as a test case because of the availability of real data from this region of both population counts at a sub-ward level, as well as the spatial location of actual COVID-19 cases from 6 April to 1 May 2020, and because Sankalitnagar represents a microcosm of Ahmedabad, with areas of both high and low urban residential densities (including informal settlements). Note that the number of cases during this period was limited (i.e., a total of 22 cases); however, we used this to test whether knowing their specific locations did indeed impact outcomes as opposed to randomly selecting infected individuals from the same location (note: to maintain confidentiality as required by the Ethics Review, the actual recorded locations were randomly shifted by 50 m in any one of eight cardinal directions). Our model thus provides important insight into the effectiveness of lockdowns and mask-wearing as mitigation measures for future pandemics, particularly in the developing world where data can be scarce. Further, information about how the effectiveness of the lockdown measures varying by housing and population densities, as well as potential mobility based on social class, can be ascertained via the ABM.

2. Study Area

With a population of nearly 8 million people, Ahmedabad is the largest city in the state of Gujarat and the seventh largest city in India [28]. Founded in the early 1400s, Ahmedabad was traditionally a walled city filled with both low-density and high-density housing structures. The high-density structures were known as "Pols", and many of the

original buildings still exist and are occupied. These Pols were originally made up of a front entrance and rooms for business and socializing, a courtyard that connected to a kitchen and washroom, and bedrooms behind the courtyard to house a few families. As the population of Ahmedabad grew, new floors were added on top of the original structures, creating crowded housing that shared common spaces and facilities. Today, traditional Pols have the highest population densities found within the city of Ahmedabad [29].

More recently, the city has started to expand beyond the walled city under British rule and is one of the fastest growing cities in India, with an increase of two million people and over 250 square kilometers from 2001 to 2011 [30]. In this expansion, formal low-density housing structures were built to accommodate the growing population. However, sections of informal high-density housing, known as "informal settlements" or more colloquially as "slums", also sprang up as marginalized members of society constructed their own housing structures.

These informal settlements are characterized by an extreme residential density, with "temporary structures, overcrowding, insecure tenure, and "lack of access to water, sanitation, and social amenities" [31]. In Gujarat, almost two-thirds of slum households (the majority of which have four or more individuals) live within one room, making the isolation of an infected individual impossible. According to the Indian 2011 census, 43% of households in informal settlements across the nation did not have access to water on the premises. A study from 2016 predicted that approximately 70% of households in informal settlements did not have a toilet on the premises [32]. This sharing of resources puts an already vulnerable population at further risk of disease spread and makes adhering to the rules of a lockdown nearly impossible.

While there are still informal settlements in Ahmedabad today, a large majority have been converted into public housing by the Slum Networking Project, a project "working for the rehabilitation and redevelopment of the urban poor" by providing "alternative housing accommodation by the developers at no cost" to slum dwellers [28]. This project encompasses a wide variety of municipal policies and has had great success. For example, under the Gujarat Slum Rehabilitation Policy, the Ahmedabad Municipal Corporation reports that "4908 houses in 11 different slums" have been constructed. These houses are a vast improvement over the informal settlement structures (providing resources like running water and ventilation) and offer a path to integration into formal society. However, they are still examples of high-density housing, with family members often living in one or two rooms and common spaces like washrooms and kitchens being shared [33], just as seen with the Pols.

3. Methods

3.1. Housing Density Classification

To better understand the distribution of housing types across the city as a precursor to the ABM simulation, remote sensing techniques were used to classify a satellite image based on density. PlanetScope imagery with a pixel size of three meters by three meters was downloaded from PlanetLabs (https://www.planet.com, URL; accessed on 13 August 2022) and clipped to six city "zones" derived from the Geomatics department of CEPT University.

Within each zone, five regions of interest were identified: dirt, high-density housing, low-density housing, roads, and vegetation, with areas deemed irrelevant (such as rivers, landing strips, or stadiums) masked out. It was possible to differentiate between high-density housing (which represents informal settlements, pols, and public housing) and low-density housing by roof types. High-density living spaces often have tin, wood, or tarped roof structures, which have a different spectral reflectance compared to the concrete or tile roofs found in other less dense neighborhoods (i.e., middle-class and wealthy) in Ahmedabad.

A portion of the selected regions of interest was verified using Google Earth satellite imagery, which has a significantly smaller pixel size, allowing a clearer depiction of the regions of interest. Once compared to Google Earth imagery, the selected regions of interest

(i.e., high-density and low-density areas) of Ahmedabad were used to train a maximum likelihood classifier to perform a supervised classification using the ENVI Image Processing and Analysis software (Figure 1).

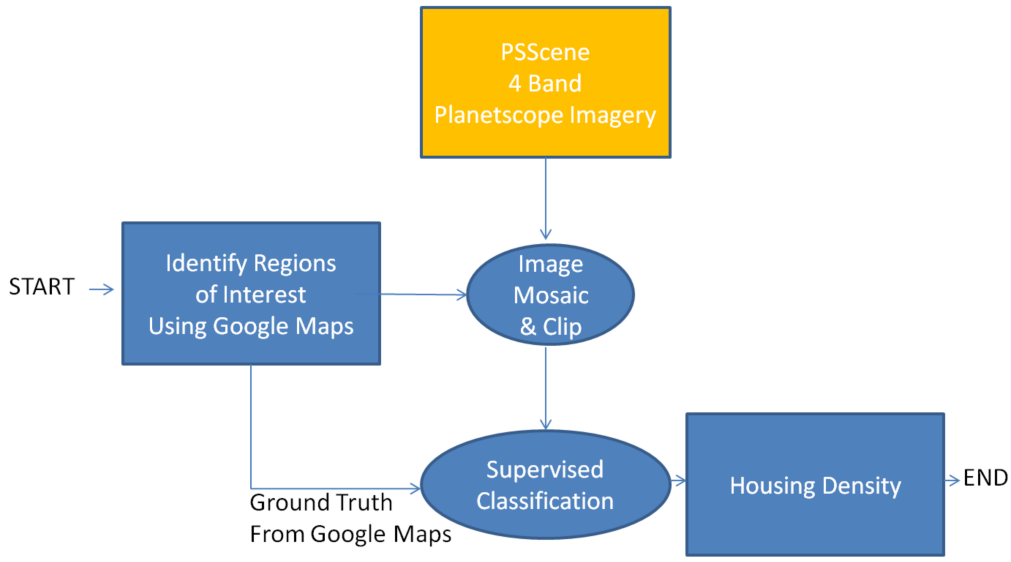

Figure 1. Workflow model of maximum likelihood classification in ENVI.

3.2. Population Density Estimations for Sankalitnagar

There is limited literature and public information available that provides details on the housing and living conditions in Sankalitnagar. Thus, the majority of this information came from family health and population surveys carried out over the course of the pandemic at the urban health centers by one of the co-authors (Qureshi, personal communication). These surveys identified: (a) the geographic location of urban health centers throughout Sankalitnagar; (b) a numeric estimate of the population each health center served; and (c) the spatial boundary of that population. The survey also identified areas of Sankalitnagar that were at a high risk of disease and other health issues, with some of those areas classified as informal settlements. This provides valuable information on population density estimates throughout Sankalitnagar and, combined with the housing density classification conducted for the area, forms the basis for the ABM simulation.

3.3. Agent-Based Modeling (ABM) of COVID-19

3.3.1. Agents

The agents in the model represent individual persons who have the potential to contract and transmit COVID-19 to other individuals/agents. These agents are spatially referenced to Sankalitnagar, which constitutes the spatial basis for the environment within the simulation. Further, the environment (i.e., Sankalitnagar) is divided into low- and high-density housing areas using satellite imagery; this classification was subsequently used to create differential rules of mobility and contact rates as described in Section 3.3.5.

3.3.2. Modeling Interface

To create the model itself, we chose the software NetLogo 6.3.0, a "programmable modeling environment for simulating natural and social phenomena" [34]. We chose this program and version because it has a GIS extension that allows the creation of spatially explicit ABMs. We also chose this program because it allows for a high amount of user input, giving us the ability to change variables within the model easily. For example, before our model is run, the user is required to make decisions regarding the introduction of COVID-19 to the agents, the movement dynamics of the agents, and adjusting the transmission rate by making decisions regarding transmission factors like the wearing of masks. The source code is provided in Appendix A.

3.3.3. Environment

The environment of the model consists of the region of Sankalitnagar, within the city of Ahmedabad, Gujarat, India (population 113,173). There are two main layers: a shapefile of Sankalitnagar and each of the ten sub-wards (Figure 2), and a raster layer housing areas as determined by a classification of satellite imagery. This classification of housing densities does not represent individual housing sites, but rather a continuous categorization of the pixels that make up the layer. This implies that within a single pixel, there could be multiple housing sites. However, within each subsection, the agents associated with that subsection are coded to be evenly distributed among the available housing pixels. This means that the agent population associated with, for example, low-density housing in any subsection would be evenly distributed among the total number of pixels classified as low-density housing within the vector feature representing that specific subsection.

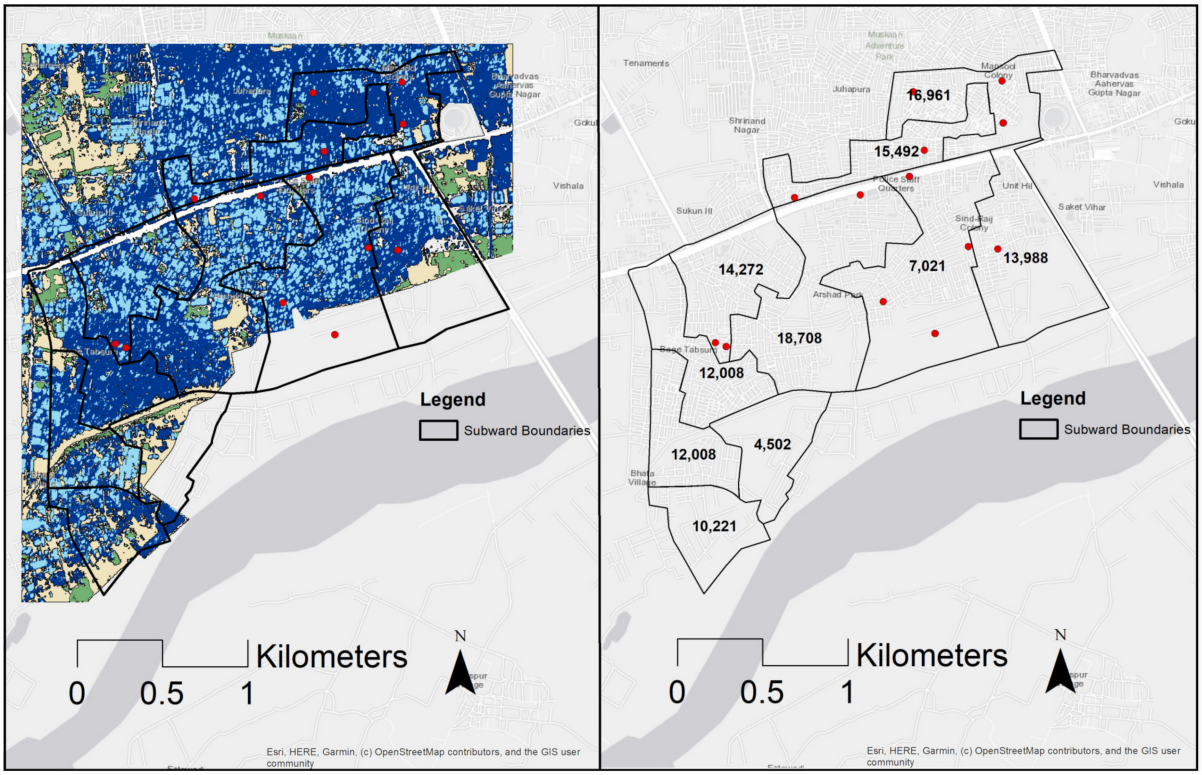

Figure 2. Maps displaying a raster layer of housing density areas on the left (high density in dark blue and low density in light blue); and a vector layer showing the approximate distribution of cases (red dots) and population totals of Sankalitnagar subwards on the right.

The model is coded so that every pixel has two associations: its housing density and the individual sub-ward of Sankalitnagar that the pixel falls into. Consequently, agents are "spawned" by the pixels, giving each agent an associated housing density and subsection of origin as well. Each subsection is coded to spawn a particular number of agents, with that number being derived from the population survey (Qureshi, personal communication), details of which are reported in Section 3.2 above. Each sub-ward of Sankalitnagar is also coded to spawn $^{1}/_{3}$ of these agents from low-density housing pixels and $^{2}/_{3}$ from high-density housing pixels based on the population distributions, and representing the individuals that live within that subsection (Figure 2 and Table 1). Moreover, the model is initialized by either a random selection of 10% of the population or using the known locations of a total of 22 cases that were reported from this area between 6 April till 1 May 2020 by the municipal government of Ahmedabad. The reported cases were of individuals who were hospitalized for COVID and excluded those who did not require hospitalization. For each case reported, details about the individual (name, age, symptoms) as well as their

exact location of residence were recorded. On 24 April 2020, India's Ministry of Home Affairs deployed a team from the National Disaster Management Authority to Ahmedabad to take over the monitoring of COVID-19 in the city. Under orders from this team, details and locations about individuals contracting COVID-19 were no longer recorded in the month of May and beyond [https://www.newindianexpress.com/nation/2020/Apr/24/COVID-19-centre-sends-four-interministerial-teams-to-gujarat-telangana-tn-2134737.html (accessed on 16 June 2024)]. Thus, these 22 cases are the only real-life case data points available from the pandemic for this neighborhood, and they are recreated spatially and temporally in the model after shifting them randomly by 50 m in any one of the eight cardinal directions to preserve confidentiality (as required by the application approved by the Ethics Review Board). Note that some locations may have recorded more than one case, these are represented as a single point. The main purpose is to understand if the use of the approximate location of known cases for model initialization has any impact on the final outcome of the ABM simulation (as compared to randomly selecting individuals to create an initial population of infected people).

Table 1. Population distributions of subwards and percentages of high- and low-density regions.

SubWard	Population	High Density (%)	Low Density (%)
1	15,492	71	29
2	14,272	61	39
3	18,708	64	36
4	16,961	82	18
5	13,988	75	25
6	7021	60	40
7	10,221	69	31
8	12,008	71	29
9	4502	69	31

3.3.4. Agent Movement

NetLogo tracks the simulation via "ticks", which can be used to represent discrete units of time (such as hours or days) through the continuous simulation. For example, one execution simulates a period of 90 days, with each tick representing one day and one night. Within each tick, the agents are assigned a location and then "walk" (take the most direct path) to that location and then "walk" back to the location they were spawned, simulating how an individual might leave the house during the day and then return at night. If there are other agents located in the pixel that falls along that path, then those agents are noted to have come in contact with the "walking" agent. The locations to which these agents are assigned are dependent on the chosen "transmission scenario," which are situational sections of code that can be activated by the user and are meant to simulate how the agents might move under different lockdown conditions that were present throughout the pandemic (Table 2).

Hence, within a single run of the model, the agents move according to the rules of the prescribed scenario. These rules are different for agents spawned from high-density and low-density housing pixels. There are three scenarios available within the model: no lockdown, partial lockdown, and lockdown. The rules of these scenarios are meant to represent real-life movement restrictions implemented by the Gujarat government at various points during the pandemic.

Table 2. Agent dynamics according to each movement restriction scenario.

Scenario	
"No Lockdown"	The low-density population is able to move within their own subsection of Sankalitnagar, while the high-density population is able to move throughout any subsection. This is meant to represent domestic work and other services provided by residents of high-density regions to residents of low-density regions.
"Partial Lockdown"	Both the high-density and low-density populations are only able to move within their own subsection and housing density classification. Agents classified as high-density are only able to move to patches classified as high-density within their own subsection, and agents classified as low-density are only able to move to patches classified as low-density.
"Lockdown"	Both populations stop moving.

3.3.5. Disease Transmission

The disease transmission of COVID-19 among the agents is also affected by user input, with the primary decision being the source of the introduction of COVID-19 to the agent population. This decision is controlled by the variable "initial-sick-population" (Table 3).

Table 3. Description of possible introductions of COVID-19 to the agent population.

Initial-Sick-Population	The Randomly Selected Initial Population Considered as Being "Sick"
"Random Population"	Upon setup of the model, a percentage of the agents will be randomly infected with COVID-19. This percentage can be adjusted using the "%-population-infected-at-start" slider. For our simulations, this variable was always set at 10%.
"From Government Data"	Infected agents will sprout not upon setup but as the model runs because these infected agents represent real-life case data with actual dates and locations.

Once the disease is introduced to the agent population, it spreads among the agents as they move around their neighborhoods (Figure 3). Within this model, all infected agents are considered contagious, and can infect other agents that are their 'neighbors', which NetLogo defines as any agents that are in the "eight patches that surround an agent's current patch" [34].

When an infected agent encounters one of its neighbors, that neighbor has a certain percent chance of contracting COVID-19. This percentage is dependent on the "wearing-mask" switch. If the switch is off the agent has a 52% chance of contracting COVID, and if the switch is on, this is lowered to 7%. These percentages are based on a systematic review of multiple studies on the efficacy of face masks in mitigating COVID-19 transmission [35]. Because the model simulates only the early part of the pandemic, well before vaccine availability on 16 January 2021, masking and social distancing/isolation are the only two mitigation techniques considered [36].

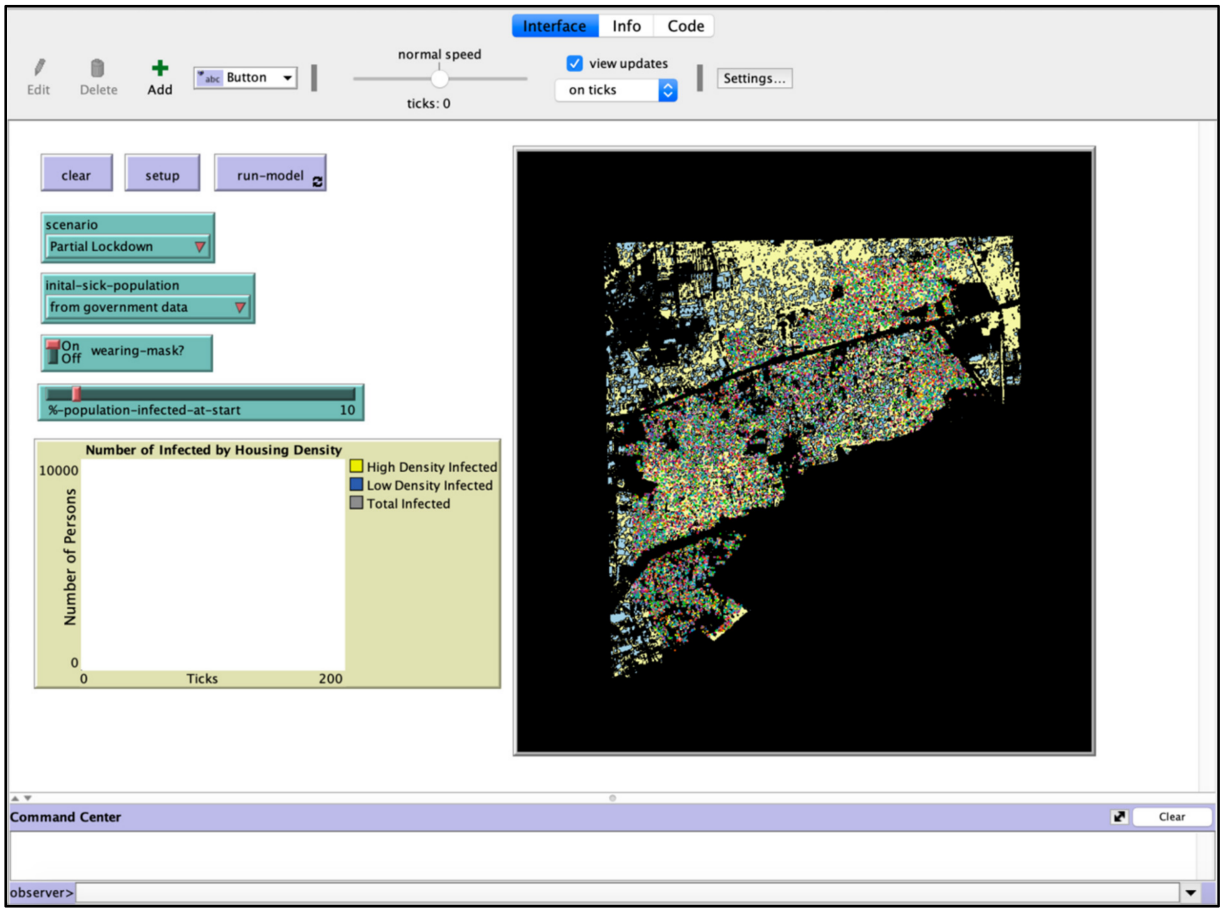

Figure 3. NetLogo Interface with agents spawned (high density housing areas in yellow, and low density housing areas in blue).

3.3.6. Initialization and Verification

To run our simulation, we used the tool Behavior Space, a module within Netlogo 6.3.0 that allows the user to run a model multiple times while "systematically varying the model's settings and recording the results of each model run" [37]. This allows comparisons of the results of the model under different transmission and initial infection scenarios.

Within Behavior Space, two experiments were executed, one for each "initial-sick-population" option, that is, either by random selection of 10% of the population as being infected or starting with 22 cases with known spatial locations (Tables 4 and 5). This allows an evaluation of how the transmission of COVID-19 across each population changed depending on the scenario and if the agents were wearing masks. Each simulation was run for exactly 90 ticks, representing 90 days, before the conditions of the experiment changed. Once a simulation is complete, Behavior Space outputs the programmed results of that simulation to a .csv file.

Table 4. Conditions for each simulation run in Behavior Space as part of experiment 1.

Initial-Sick Population	Scenario	Wearing-Mask?
"random population"	No Lockdown	TRUE
"random population"	Partial Lockdown	TRUE
"random population"	Lockdown	TRUE
"random population"	No Lockdown	FALSE
"random population"	Partial Lockdown	FALSE
"random population"	Lockdown	FALSE

Table 5. Conditions for each simulation run in Behavior Space as part of experiment 2.

Inital-Sick Population	Scenario	Wearing-Mask?
"from government data"	No Lockdown	TRUE
"from government data"	Partial Lockdown	TRUE
"from government data"	Lockdown	TRUE
"from government data"	No Lockdown	FALSE
"from government data"	Partial Lockdown	FALSE
"from government data"	Lockdown	FALSE

Since the goal of this study was to understand the infection rates of COVID-19, specifically across housing densities, Behavior Space runs were programmed to measure for each tick the total number of infected agents, the total number of infected agents who were associated with high-density housing, and the total number of infected agents who were associated with low-density housing. Thus, two experiments were programmed, each with six simulations, and each simulation had three sets of data with 90 data points in each set. This provided a detailed look into the transmission rates of COVID-19 across a three-month (i.e., 90-day) period under a wide variety of conditions.

4. Results

4.1. Model Runs

The results obtained for each of the three scenarios (lockdown, partial lockdown, and no lockdown) under the conditions of wearing and not wearing masks are compiled and presented in Figures 4 and 5. Notably, there is no difference between initializing the model by randomly selecting individuals (experiment 1) and the 22 cases with known locations (experiment 2), except for the fact that the number of infections is initially higher in experiment 1 (due to a higher initial number of cases). However, both experiments yield similar graphs of cases, suggesting that knowing the spatial location of initial cases is not as important for affecting disease spread. The most striking result in both sets of experiments is the significant decrease in transmission rates when the agents were coded to be wearing masks, regardless of the movement scenario or housing densities. This phenomenon is best represented by the results of experiment one, which was informed by real-life COVID-19 case data, specifically under the "no lockdown" movement scenario. Without masks, 100% of the population was infected with COVID-19 within 60 days. With masks, less than 5% of the population was infected by that same date (Figure 5A,D).

However, a more nuanced understanding of the results highlights differences between high- and low-density areas, especially under a partial lockdown scenario. When there is a partial lockdown and people are not wearing masks, the increase in cases simulated based on a random 10% of the population is greater in high-density areas, reaching ~67% after about 20 days, than in low-density ones (which reach ~30% in the same period). This is even more striking when the simulation uses an initial population obtained from real-world data (Figure 5), with the only difference being a later start to the rise in infections (due to low initial rates of infection in real-world data). In this case, without masks, 100% of the population was infected with COVID-19 within 65 days. With masks, only 2.73% of the population was infected by that same date (Figure 5A,D).

Furthermore, there is an overall decrease in transmission that applies to both the high- and low-density areas equally when one considers the continuum of the three scenarios, i.e., the "no lockdown" scenario, the "partial lockdown" scenario, and the "lockdown" scenario, regardless of other variable conditions. In experiment 1, there was an average decrease of 73% in the final number of total cases between simulations with a "no lockdown" scenario and a "lockdown" scenario. In experiment 2, there was an average decrease of 94% between the simulations and the respective scenarios. In all simulations under a "lockdown" scenario, all three dataset trends (of total infected, high-density infected, and low-density infected) approach or reach a plateau before the end of the simulation, supporting the

hypothesis that restricting movement restricts transmission even in high-density and crowded living environments.

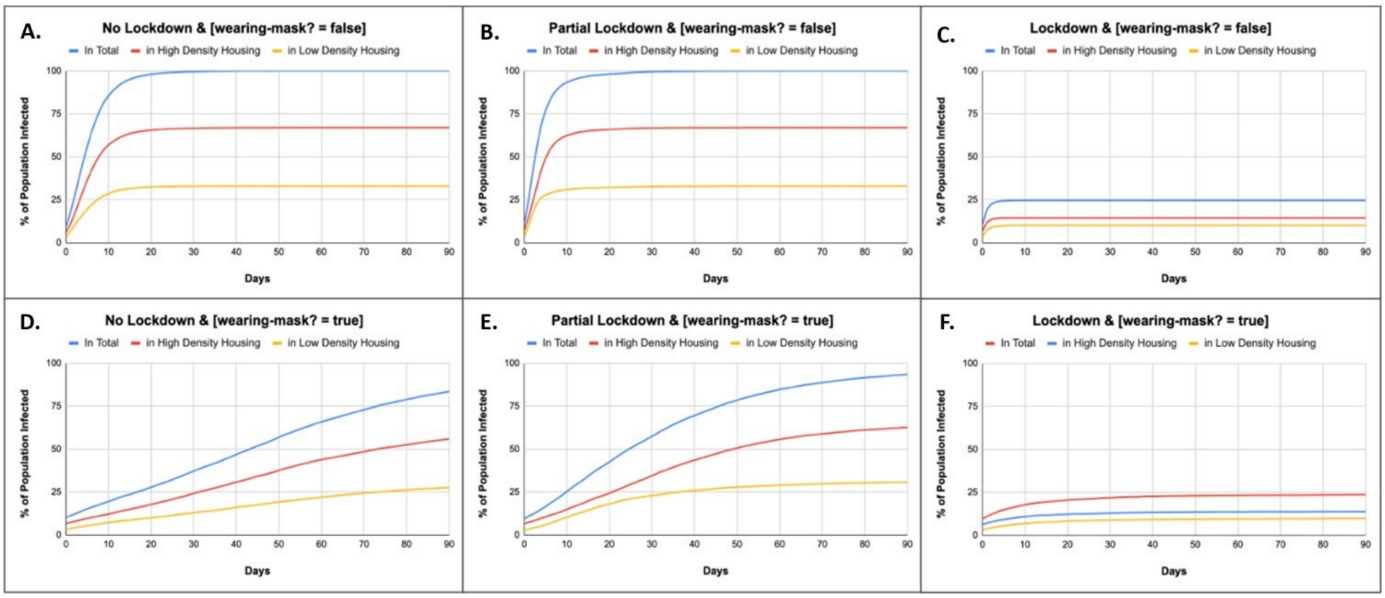

Figure 4. Results for a 90-day simulation based on an initial infection of a random 10% of the population when it considers (**A**) no lockdown & no masks (**B**) partial lockdown but no masks (**C**) complete lockdown but no masks (**D**) no lockdown but with mask mandates (**E**) partial lockdown with mask mandates and (**F**) complete lockdown with mask mandates.

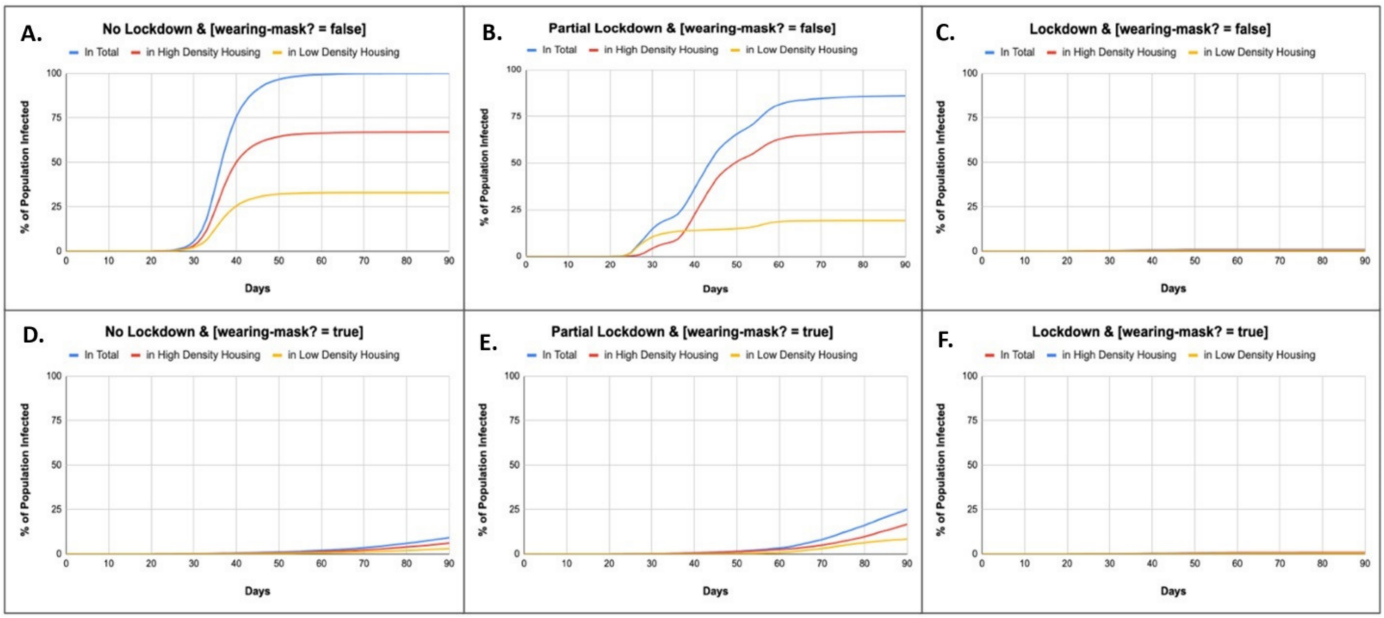

Figure 5. Results for a 90-day simulation based on an initial infection of the population according to the 22 cases when it considers (**A**) no lockdown & no masks (**B**) partial lockdown but no masks (**C**) complete lockdown but no masks (**D**) no lockdown but with mask mandates (**E**) partial lockdown with mask mandates and (**F**) complete lockdown with mask mandates.

For example, in experiment 1, even without masks, the percentage of infected individuals from the high-density population to the total population plateaus within ten days of the start of the simulation, staying consistent at 14% until the simulation concludes (Figure 4C). With masks, this percentage has an initial surge at the start of the simulation that eventually tapers out to end at 13%, suggesting that the trend line of infections in

high-density areas is approaching the plateau demonstrated in the previously discussed simulation (Figure 4E). Further, there is a noticeable phenomenon in which the infection rates increase at a higher rate under the "partial lockdown" scenario compared to the "no lockdown" scenario (Figure 4D,E).

Under the "no lockdown" scenario, agents are free to move to patches within their own subsection or the other subsections, regardless of the housing density associated with those patches. Under the "partial lockdown" scenario, all agents are confined to their own subsection and can only move to patches within that subsection that have the same associated housing density as themselves (i.e., high-density agents can only move to high-density patches and vice versa).

The "partial lockdown" scenario was coded to account for the real-life difficulties of enforcing a lockdown, especially in urban spaces. While governments can easily enforce the closing of businesses and public transportation, it is much more difficult to prevent people from interacting with their neighbors. This is particularly true for high-density housing (including Pols), where some facilities (e.g., communal water taps, toilets) may be shared. Furthermore, when businesses are closed and movement is restricted, individuals become more reliant on their social network for the sharing of resources, increasing transmission within a neighborhood. This effectively expands their "bubble" to include multiple households. Thus, this form of unavoidable interaction could conceivably cause a higher infection rate in the population than assuming a total lockdown. This is demonstrated in Figure 6, which shows linear trend lines for two simulations from experiment 1, with both simulations showing that the variable "wearing-mask?" is equal to true, but varying according to the movement scenario (i.e., "no lockdown" versus "partial lockdown").

The same phenomenon is noted in Figure 7, which shows linear trend lines for two simulations from experiment 2 with the same conditions as the previously discussed simulations. These two simulations most closely mirror real-life COVID-19 transmission because the initial COVID-19 cases that infect the rest of the population were based on actual COVID-19 case data from the beginning of the pandemic in the spring of 2020. The trend lines for these simulations are shown in Tables 6 and 7. For each simulation, there was a steeper slope of the trend line when the movement scenario was "partial lockdown" as opposed to "no lockdown".

Table 6. Linear equations of trend lines for the simulations run as part of experiment 1, when the simulation is initialized with a random 10% of the population.

Random Population	[Wearing-Mask?]	No Lockdown	Partial Lockdown
Total Infected (%)	TRUE	y = 0.858x + 11.7	y = 0.936x + 23.4
High-Density Infected (%)	TRUE	y = 0.581x + 7.07	y = 0.658x + 12.4
Low-Density Infected (%)	TRUE	y = 0.276x + 4.67	y = 0.277x + 11

Table 7. Linear equations of trend lines for the simulations run as part of experiment 1, when the simulation is initialized with the location of 22 cases recorded by the municipal government.

From Government Data	[Wearing-Mask?]	No Lockdown	Partial Lockdown
Total Infected (%)	TRUE	y = 0.0858x + −1.83	y = 0.223x + −5.24
High-Density Infected (%)	TRUE	y = 0.0569x + −1.22	y = 0.141x + −3.25
Low-Density Infected (%)	TRUE	y = 0.0289x + −0.605	y = 0.082x + −2

Overall, the results suggest that housing density has the most impact during a partial lockdown, particularly when people are not mandated to wear masks, with an increase in cases happening more rapidly in high-density areas than in low-density ones. This is primarily because, despite lockdown mandates, interactions between neighbors remain unavoidable due to the structure of the housing in these areas. On the other hand, when mask-wearing is mandated, the infected agents associated with high-density housing make up approximately $^{2}/_{3}$ or the population, while infected agents associated with low-density housing make up the remaining $^{1}/_{3}$. This proportion of $^{2}/_{3}$ to $^{1}/_{3}$ stays largely intact, matching real-world data. This suggests that housing density concerns could be mitigated by other prevention measures (i.e., mask wearing).

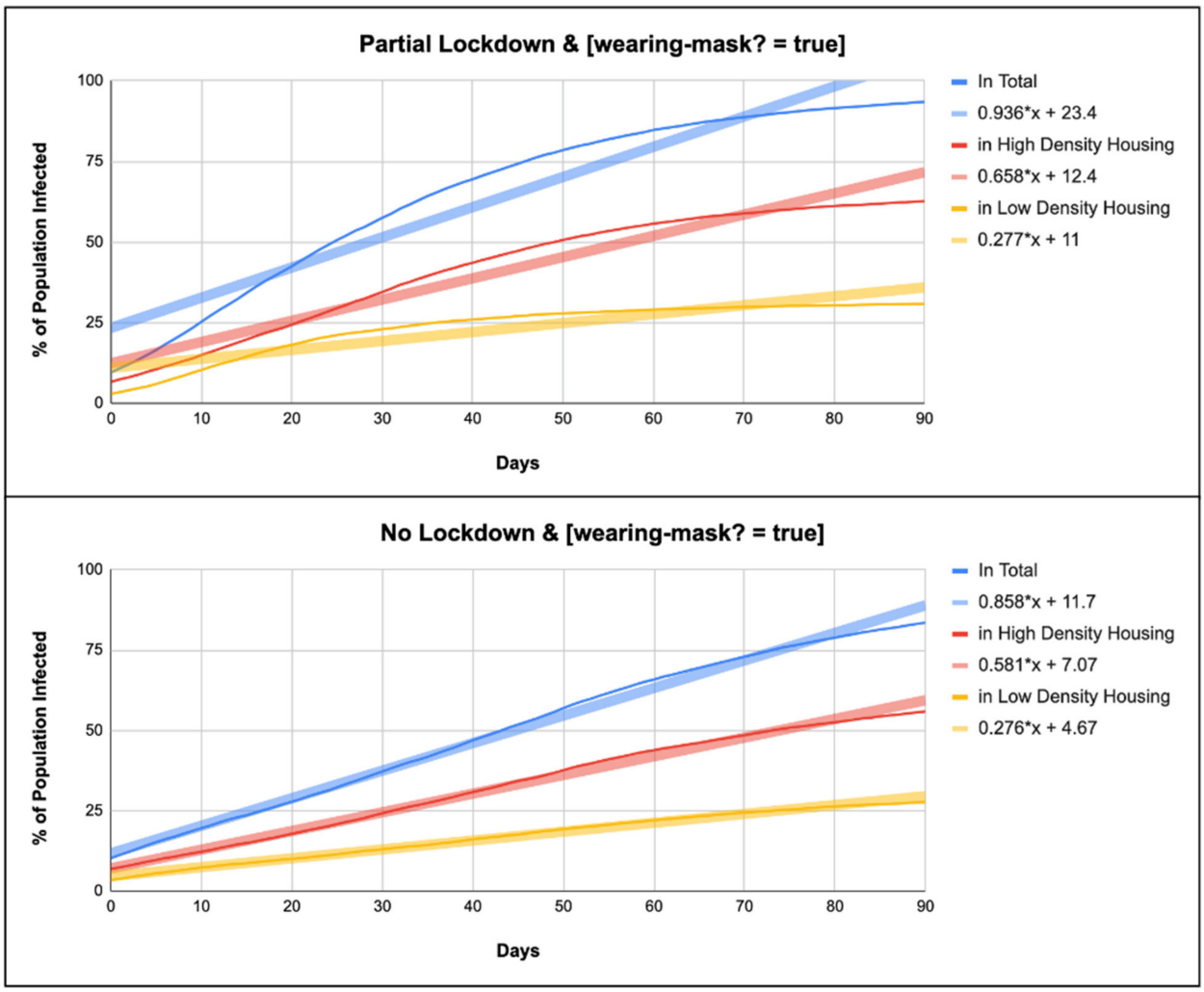

Figure 6. Comparative results of a simulation with a "No Lockdown" scenario and a "Partial Lockdown" scenario in experiment 1.

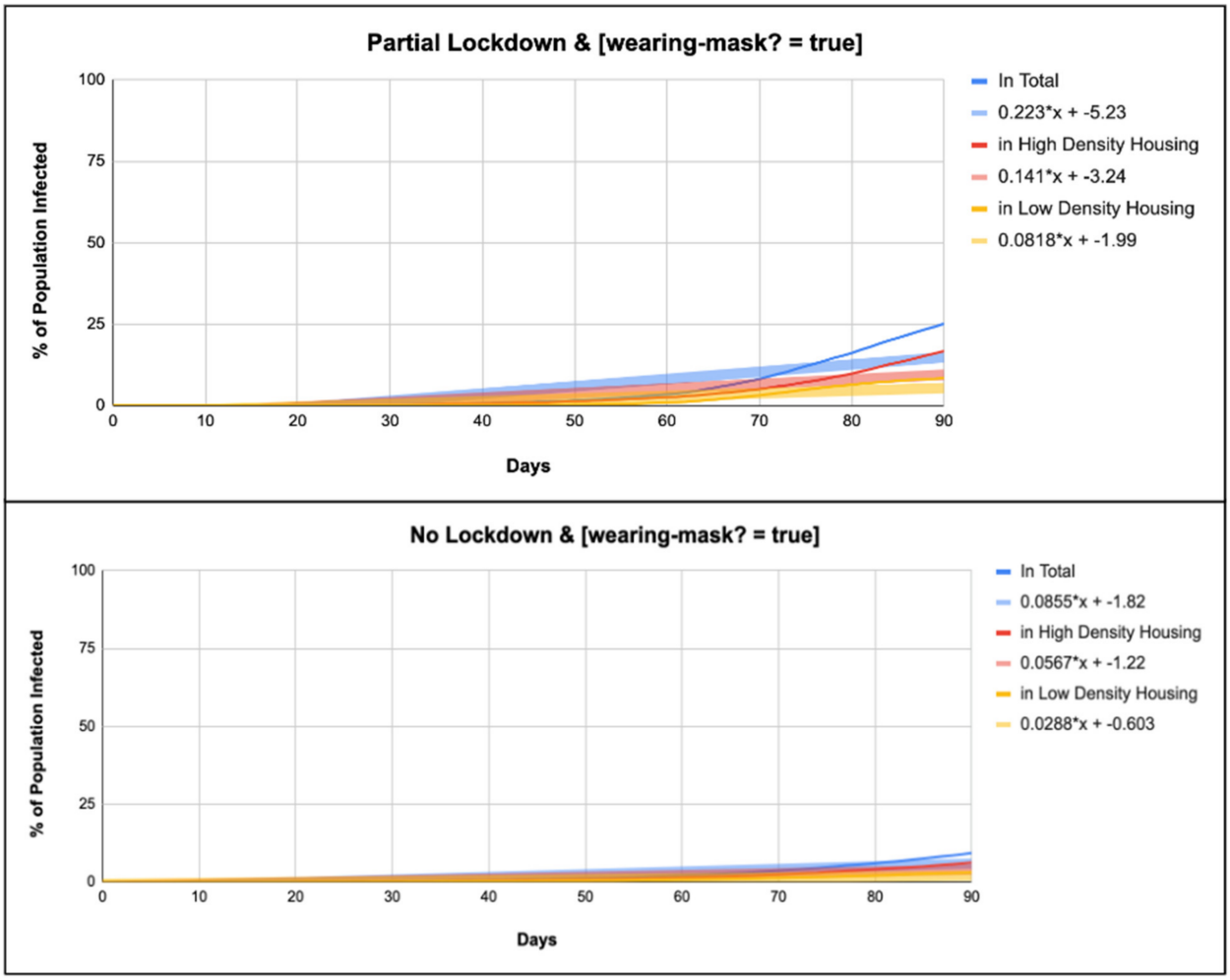

Figure 7. Comparative results of a simulation with a "No Lockdown" scenario and a "Partial Lockdown" scenario in experiment 2.

4.2. Variation in Model Output

In experiment 1, since both the initial sick population is randomly assigned and the destination location for each "walk" is randomly selected, it is important to consider the variability observed from multiple model runs. Therefore, the base model (consisting of an initial 10% randomly selected "sick" population with partial lockdown and mask-wearing) is run five times to observe variations in its output. The variability is shown in Figure 8.

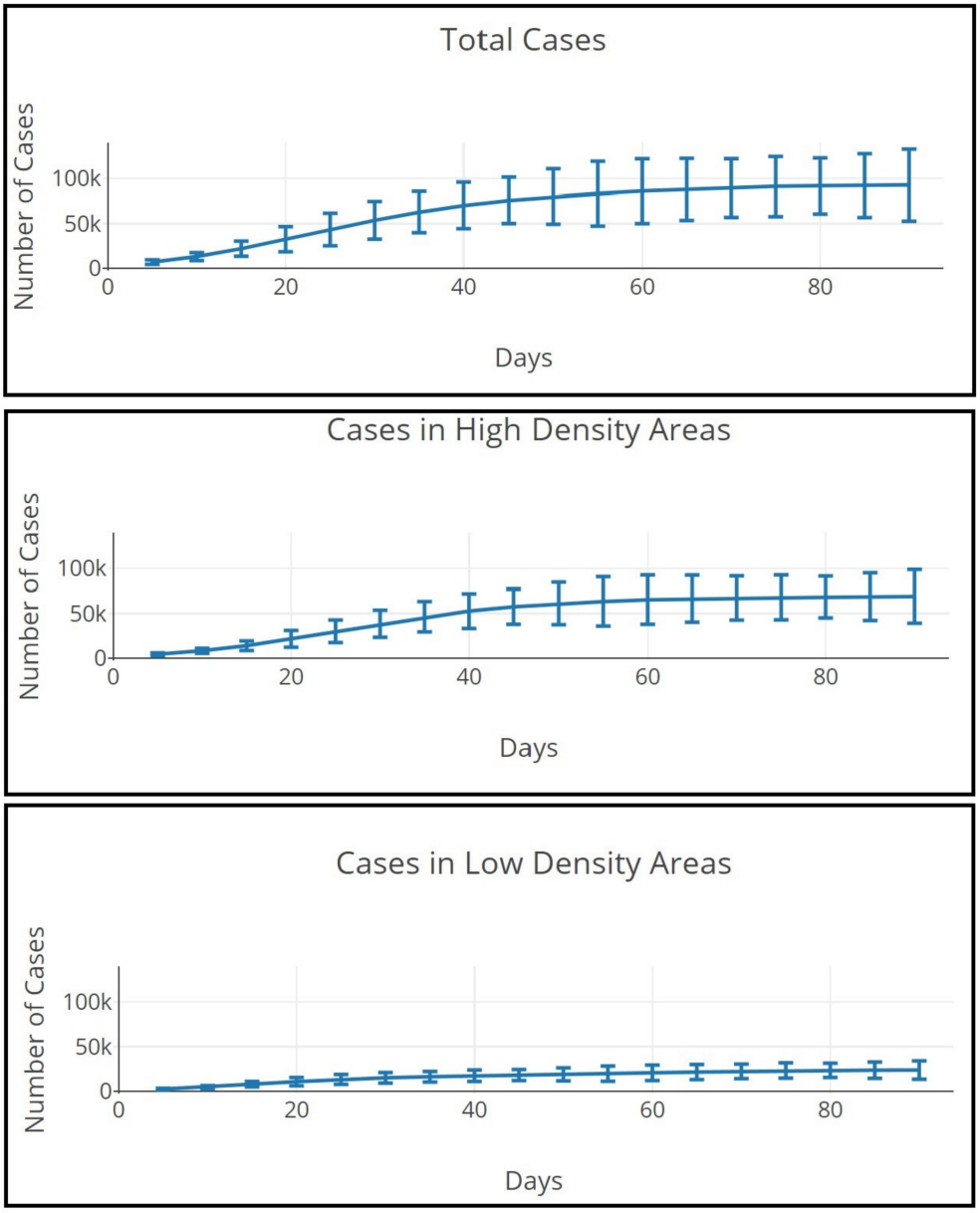

Figure 8. Average number of cases and standard deviations observed over 30 runs (using a random 10% of the population under partial lockdown and mask-wearing conditions).

5. Limitations and Future Work

This study has some significant limitations. These include (a) the small sample size of actual COVID cases used to initialize the model for experiment 2, (b) the small spatial size of the simulated neighborhood, (c) the focus on the short initial phases of the pandemic, and (d) potential oversimplification in the modeling of human behavior and movement. One of the goals of this model was to use real-life COVID-19 case data as well as actual population counts for regions of the city to initialize the model. However, this significantly limited the scope of the model because the municipal government only kept records for approximately one month (recording 22 cases requiring hospitalization for COVID in the area of interest) before it handed over management to the federal government, which stopped further data collection. Further, in attempting to tie these cases to housing density, the goal was to choose an area of the city with available population data. This information was available on a sub-ward basis only for the Sankalitnagar area of Ahmedabad, and this thus became the chosen location for the study area. Moreover, because additional policy measures such as vaccinations became common later on in the study, the model was executed only

for the initial 90 days of the pandemic. This limits the usefulness of this work for public health planning, as both individual behaviors and policy responses might have evolved significantly during the entire length of the pandemic. This can affect the robustness and temporal relevance of our conclusions, and care must be taken to limit the findings to the initial phases of the pandemic. Finally, there is potential oversimplification in the modeling of human behavior and movement, as only the movement of agents (both within and to neighboring regions) is simulated under various lockdown scenarios. The model does not account for more complex behaviors that may have been exhibited, e.g., avoidance of houses with known cases of COVID. Thus, it may fail to accurately reflect the complex and often non-linear nature of human interactions in densely populated urban environments.

Thus, in future work, the recommendation is to collect finer-scale data and simulate communicable diseases at the household level rather than at the neighborhood level. This would not only allow for a more detailed and accurate model, but also allow for the expansion of the model to account for agent interaction that might occur outside of an agent's residential neighborhood. Further, it calls for more detailed information at the household level to be available for simulating communicable diseases and, if possible, to parameterize the model to run at the household level. Additional consideration should also be given to the complex human interactions in densely populated urban environments [38]. This will ensure that a well parameterized, spatially explicit ABM model can be built to understand the finer-scale dynamics of disease spread.

6. Discussion and Conclusions

It is evident from the simulations that the realistic scenario of "partial-lockdowns" would have caused significant increases in cases in high-density housing without additional preventative measures such as mask-wearing. Overall, both lockdowns and mask-wearing were effective in reducing the number of infections in both high- and low-density housing neighborhoods. Further, the model was parameterized using, and was able to readily replicate, the initial spread of COVID-19 infections between 13 March and 1 May 2020. Since no additional data about COVID-19 cases were released after this date, further validation of ABM results after this date was not possible. More importantly, model runs with and without initial data about the location of COVID-19 cases showed no difference, suggesting that the initialization of the model with the actual location of cases is not an important factor.

There were some interesting findings from the simulation results relating to the preventative measures. First, there were significant differences between wearing masks and not wearing masks in the "no lockdown" scenario. Without masks, in both experiments, 100% of the population was infected with COVID-19 within 65 days. With masks, only 2.73% of the population was infected in the same period, indicating that masks were an effective means of reducing spread. Additionally, only the full lockdown scenario reduced the total number of infections recorded as compared to even the partial lockdown scenario. This is because, as stated earlier, there are social interactions that continue to happen between neighbors in high-density settings that increase cases. Both of these findings are in line with a meta-analysis reported in the literature [39].

These can be further elucidated by understanding the nuances of model setup. First, as expected, there were differences in rates of infection between total, partial, and no lockdown scenarios. But while a total lockdown was effective in reducing the total numbers of infected individuals in both low- and high-density housing regions, partial lockdowns were less successful in high-density regions. As the agents continued to interact with their neighbors during a "partial lockdown" scenario, the rates of infection continued to increase, even exceeding the rates of the "no lockdown" scenario. Thus, in high-density housing environments, any "partial lockdowns" (which does not account for shared resources with neighbors) are particularly ineffective. This finding is significant to public health policy, as it demonstrates that cities like Ahmedabad should plan ahead for epidemic management

in regions with high-density housing, perhaps by distributing masks and sanitizers early to help reduce the spread caused by shared resources.

Second, findings from the simulation indicated that mask-wearing was highly effective, irrespective of housing densities. While this seems counterintuitive (particularly with the focus on housing density), these findings replicate other studies that have found similar results at the neighborhood level [40,41]. Specifically, Almagro and Orane-Hutchinson [41] reported that "crowding of shared spaces (i.e., the number of individuals constituting households) plays a more important role than simply the density of locations". Indeed, the number of individuals per household may better represent the crowding of shared spaces; however, these estimates were not available for parameterizing the simulations presented here. Thus, the housing density estimates used in this work are neighborhood-level measures, and these seem insufficient to properly represent the finer scale of "within-household" dynamics. Despite this, findings from the simulation show promise for masking as a mitigation effort in high-density spaces and suggest that ensuring the widespread availability of masks and sanitizers is a cheap and easy investment for cities to make for future pandemic preparedness.

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Data Availability Statement: Due to confidentiality reasons, the original data of COVID cases and their locations cannot be made available. However, the code for the ABM model is provided in Appendix A.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Netlogo Source Code

The original Netlogo source code is provided below:

```
;SETUP ----------------------------------------------------------------
extensions [gis profiler]

breed [low lows]
breed [high highs]
breed [sick sicks]


globals[
;globals representing datasets
housing
```

```
    buffer
    cases
    density
    buffer-coords
    boundary


    ;global representing ticks
    counter

    ;globals representing patches
    high-patches
    low-patches
    neighborhood-patches
    boundary-patches

    high-density-turtles
    low-density-turtles
]

patches-own[
  high-density?
  low-density?
  patch-ID
]

turtles-own [
    origin
    origin-xy
    origin-x
    origin-y
    origin-patch
    sick?
    recovered?
    symptomatic?
    infected?
    infectious?
    origin-ID
    exposure-date
    sick-duration
    incubation
```

```
    high-density-t?
  low-density-t?
]

to load-data
    __clear-all-and-reset-ticks ;clear remains of previous runs

  load-housing
  load-features

  gis:set-world-envelope (gis:envelope-union-of (gis:envelope-of boundary)
                                                (gis:envelope-of buffer)
                                                (gis:envelope-of cases)
                                                (gis:envelope-of housing))
  set counter 0
end

to load-features
  set boundary gis:load-dataset "Shapefile_Simplified_Density.shp"
  set buffer gis:load-dataset "Shapefiles_1kmbuffer.shp"
  set cases gis:load-dataset "CovidCases_1kmbuffer.shp"
end

to load-housing
  set housing gis:load-dataset "ml_1_arcmap_gcs.asc"


  ;gis:load-coordinate-system "/Users/mollyfrench/Desktop/Sankalitnagar Model/FINAL
MODEL_1/FINAL MODEL/Data/Shapefiles from Dr. Quereshi/Shapefile_Simplified.prj"
end


;HOUSING ------------------------------------------------------------------
to apply-housing
  ;resize-world 0 gis:width-of (housing) 0 gis:height-of (housing)

  gis:apply-raster housing density

  ;resize-world 0 gis:width-of (housing) 0 gis:height-of (housing)

  ask patches [
    set density gis:raster-sample housing self
```

```
      if (density = 42)[
        set high-density? true
        set pcolor 48
      ]
      if (density = 53) [
        set low-density? true
        set pcolor 98
      ]
    ]
end

to sample-housing
    ask patches [
      set density gis:raster-sample housing self
      if (density = 42)[
        set high-density? true
        set pcolor 48
      ]
      if (density = 53) [
        set low-density? true
          set pcolor 98
      ]
    ]
end

;SETUP POPULATION ------------------------------------------------------------------------
to apply-population-evenly

  set boundary-patches (patches gis:intersecting boundary)

  foreach gis:feature-list-of boundary [
      neighborhood ->

      ;Get the population for a high density neighborhood, take 2/3 of population
      ;FOR NOW DIVIDE BY 100 AND ROUND
      let high-density-pop round ((gis:property-value neighborhood "HIGH_POP") / 10)
      let low-density-pop round ((gis:property-value neighborhood "LOW_POP") / 10)
      let neighborhood-pop round ((gis:property-value neighborhood "POP") / 10)

      set neighborhood-patches (patches gis:intersecting neighborhood) with [gis:contained-by? self neighborhood]
```

```
    ask neighborhood-patches [set patch-ID gis:property-value neighborhood "Id"]

    set high-patches (patches gis:intersecting neighborhood) with [gis:contained-by? self neighborhood] with [high-density? = true]
    set low-patches (patches gis:intersecting neighborhood) with [gis:contained-by? self neighborhood] with [low-density? = true]


    ;ask high-patches [set pcolor white]
    ask n-of high-density-pop high-patches[
      sprout-high 1[
      set origin patch-here
      set origin-ID patch-ID
      set infected? false
      set recovered? false
      set high-density-t? true]]

    ask n-of low-density-pop low-patches[
      sprout-low 1[
      set origin patch-here
      set origin-ID patch-ID
      set infected? false
      set recovered? false
      set low-density-t? true]]
      ]

end

to setup-infected-within-buffer
  ;if ticks = 0 ;;[set dt time:create "2020/3/17 00:00"]
  ;[show "Showing Covid19 Cases from 17/3/2020..."]

    foreach gis:feature-list-of cases [ vector-feature -> let day gis:property-value vector-feature "Days_Since"
    if day = counter
      [let starting-point gis:location-of(gis:centroid-of(vector-feature))

          ;set up so there is 2/3 chance that sick is part of high-density population and 1/3 chance that sick is part of low-density population
          if-else (random-float 100 < 67)
          [create-high 1[
            set size 5
```

```
            set color blue
            set xcor (item 0 starting-point)
            set ycor (item 1 starting-point)
            set origin one-of boundary-patches with [high-density? = true]
            set origin-ID [patch-ID] of origin
            set high-density-t? true

            set exposure-date counter
            set sick-duration 2 + (random 12) ;set incubation period between 2–14 days
            set infected? true
            set recovered? false]]

          [create-low 1[
            set size 5
            set color blue
            set xcor (item 0 starting-point)
            set ycor (item 1 starting-point)
            set origin one-of boundary-patches with [low-density? = true]
            set origin-ID [patch-ID] of origin
            set low-density-t? true

            set exposure-date counter
            set sick-duration 2 + (random 12) ;set incubation period between 2–14 days
            set infected? true
            set recovered? false]]
      ]
    ]
  ;set counter counter + 1

    ;ifelse ticks = 50
    ;[stop]
end

to setup-sick-populations
    ask turtles [
        if (random-float 100 < %-population-infected-at-start)[
         set exposure-date counter
         set sick-duration 2 + (random 12) ;set incubation period between 2–14 days
         set infected? true
         set recovered? false]]
```

```
end

;TO MODEL
to clear
  __clear-all-and-reset-ticks

  set counter 0
end

to setup
  __clear-all-and-reset-ticks

  set counter 0

  load-data
  sample-housing

  apply-population-evenly

  if inital-sick-population = "random population" [setup-sick-populations]

  ask turtles [
    set size 5
    set shape "person"]
end

to run-model
    ;setup initial sick population when setting up model

    if inital-sick-population = "from government data" [
      setup-infected-within-buffer]


  ;1) have turtles move according to scenario
   if scenario = "No Lockdown"[
      ask turtles with [high-density-t? = true] [
    move-to one-of patches with [patch-ID = [origin-ID] of myself]
  ]
      ask turtles with [low-density-t? = true] [
    move-to one-of boundary-patches]
```

```
  ]

    if scenario = "Partial Lockdown"[
        ask turtles with [high-density-t? = true] [
      move-to one-of patches with [(patch-ID = [origin-ID] of myself) AND (high-density? = true)]
  ]
        ask turtles with [low-density-t? = true] [
        move-to one-of patches with [patch-ID = [origin-ID] of myself AND (low-density? = true)]]
  ]

    if scenario = "Lockdown"[
        ask turtles with [high-density-t? = true] [
      stop
  ]
        ask turtles with [low-density-t? = true] [
      stop]
  ]

    ;2) after turtles move- ask them to infect one another or catagorize themselves
  ask turtles [

    if (infected? = true) ;AND (recovered? = false)
  [
    infect]

    if (infected? = true) AND (counter = exposure-date + sick-duration) [
    set recovered? true]
 ]

 ;3) have turtles return home in the evening
    ask turtles [
       move-to origin]

 ;4) ask turtles to re-infect at home
    ask turtles [
    if (infected? = true) AND (recovered? = false)[
    infect]]

  set counter counter + 1
  tick
```

```
end


;COVID-19 DISEASE SPREAD-----------------------------------------------------------
  to infect
    let nearby-uninfected (turtles-on neighbors) with [infected? = false]

      if any? nearby-uninfected [
        ask nearby-uninfected [
        if wearing-mask? = true [
          if random-float 100 <= 7 [
              set exposure-date counter
              set sick-duration 2 + (random 12) ;set sick period between 2–14 days
              set infected? true
              set recovered? false

        ]]

        if wearing-mask? = false [
          if random-float 100 <= 52 [
              set exposure-date counter
              set sick-duration 2 + (random 12) ;set sick period between 2–14 days
              set infected? true
              set recovered? false
        ]
    ]]]
end
```

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