Promoting the adoption of agent-based modelling for synergistic interventions and decision-making during pandemic outbreaks

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Abstract. Geography has long sought to explain spatial relationships between social and physical processes, including the spread of infectious diseases, within the context of modelling human-environment interactions. The spread of the recent COVID-19 pandemic, and its devastating effects on human activity and welfare, represent but examples of such complex human-environment interactions. In this paper, we discuss the value of agent-based models for simulating the spread of the COVID-19 virus to support decision-making with regards to non-pharmaceutical interventions, e.g., lock-down. We also develop a prototype agent-based model using a minimal set of rules regarding patterns of human mobility within a hypothetical town, and couple that with an epidemiological model of infectious disease spread. The coupled model is used to: (a) create synthetic trajectories corresponding to daily and weekly activities postulated between a set of predefined points of interest (e.g., home, work), and (b) simulate new infections at contact points and their subsequent effects on the spread of the disease. We finally use the model simulations as a means of evaluating decisions regarding the number and type of activities to be limited during a planned lockdown in a COVID-19 pandemic context.

Keywords: spatial simulation, lock-down, COVID-19.

1 Introduction

The extent and intensity of the recent COVID-19 pandemic, enhanced by the interconnectedness of the population due to urbanization and globalization, demonstrated the complexity of the effects of a pandemic in all areas of human life and activities. As both the spread and consequences of COVID-19 are spatially indexed and dynamic in nature, relevant application areas of GIScience concepts and methods include the visualization and analysis of the spatiotemporal distribution of infected cases, the spatiotemporal activities of individuals, mobility patterns and transportation networks, the spatial dimension of environmental conditions that enhance the spread of diseases, and the access to health care facilities (Franch-Pardo et al., 2020; Kamel Boulos and Geraghty, 2020; Zhou et al., 2020). Moreover, the recent COVID-19 pandemic has highlighted important scientific opportunities and synergies between spatial analysis, modelling and simulation with key allied scientific fields, such as epidemiology, data science, transportation, spatial planning and economics (Hsiang et al., 2020; Latif et al., 2020; Wulkow et al., 2021).

In this work, we advocate the use of simulation experiments within an interdisciplinary agent-based modelling framework, and the evaluation of scenarios related to the spread of the COVID-19 pandemic for guiding non-pharmaceutical interventions that can be spatially and temporally focused. Such decisions may include when a lockdown should be imposed or lifted, what elements of social / economic life and related activities should be restricted or enhanced, in what chronological order, and where geographically, all with a view to their potential impact on public health and the economy. We also develop a prototype agent-based model using a minimal set of rules regarding patterns of human mobility within a synthetically sketched town, and couple that model with an epidemiological model of infectious disease spread. We use model simulations to illustrate the evaluation of alternative decisions about the number and type of activities to be limited during a planned lockdown in the COVID-19 pandemic context.

2 ABMs in epidemiology

Agent-based models (ABMs) are generally defined as a computational framework consisting of autonomous agents for simulating dynamic processes (Bonabeau, 2002), commonly used to model individual decision-making and social and organizational behaviour. Agents most often represent people or groups in a community, endowed with a set of behavioural rules encapsulating their daily activities, social behaviour, and interactions with the environment and among each other.

As diseases such as MERS, H1N1 and H5N1 flues, but also the recent coronavirus (SARS-CoV-2), are transmitted from individual to individual via their contact networks in geographical space, understanding infectious disease dynamics calls for spatially explicit process models. The dynamic nature of interactions also increases the complexity of the transmission mechanisms, and consequently renders pandemic risk assessment more difficult. The process of modelling and simulating infectious disease spread in light of relevant contacts can lead to a better understanding of transmission mechanisms, while being practically useful towards the development of theories, planning of epidemiological surveys, as well as the prediction of trends, all of which could eventually prevent hasty decisions when it comes to interventions (Yang et. al., 2008; Perez and Dragicevic, 2009; Khalil et al., 2012).

Spatial ABMs are ideal for simulating the evolution of a disease within an epidemic or pandemic context (Tracy et al., 2018). Such simulations can broaden understanding regarding infectious disease transmission by highlighting patterns of interactions with other agents (Frerichs et al., 2019). In addition, ABMs are valuable tools for policy shaping and planning interventions for the benefit of public health and the economy. The more realistically a model recreates social interactions the more practical its application to real-world scenarios and the prediction of potential impacts on control measures against an upcoming pandemic will be (Wang, 2020).

The transmission levels, the incubation period, as well as the uncertainty associated with the virus detection, in combination with the increased human mobility within and between urban areas, has led to the need of scientific and technological support for the mitigation and control of its further spread (Zhou et al., 2020). Given the bottom-up nature of ABMs, their use for modelling a pandemic has recently expanded, providing further insights on mechanisms that produce spatiotemporal patterns of disease cases while taking into consideration the heterogeneous behaviour of individuals and related social networks (Hunter et al., 2018).

Despite their advantages, ABMs suffer from several drawbacks. In particular, data on population activities and on the stochastic nature of infectious disease spread are often sparse or unavailable (Yang et al., 2008). The use of big data, e.g., telecommunication and social network data, for tracing of human mobility is gradually helping to overcome related issues, although their reliability is often questioned (Venkatramanan et al., 2018). Moreover, lifting the restrictions of personal data protection is not always feasible. The behaviour of individuals in space and the tracking of their movement often presents various degrees of deviation from area to area due to variations of demographic and socioeconomic characteristics. Developing ABMs that encapsulate realistic individual behaviour taking into account social background and adaptation to pandemic conditions is therefore challenging.

3 Coupling ABMs with epidemiological models

The temporal evolution of the spread of a disease over a population is widely modelled via the Susceptible, Infected, Removed or recovered (SIR) epidemiological model and/or its various extensions (Hethcote, 2000). The basic version of the SIR model includes three health states which group individuals in three population compartments (see Figure 1):

- Healthy but vulnerable to disease; susceptible (S)
- Infected (I)
- Removed or recovered (R)

Figure 1. The three epidemiological states of a SIR model.

Term β (beta) controls the transition between stages S and I while term γ (gamma) affects the transition between stages I and R.

SIR models (and their extensions) typically treat each compartment of the population as a homogenous group of people that live and move in a homogeneous geographical area. Although efforts have been made to extend SIR models by incorporating additional functionality, such as age groups or other individual features, the integration of the spatial component, i.e., geographical variability, in such models is still under

development. Integrating spatial variability in SIR models can bring significant benefits in understanding the most important factors in the transmission of infectious diseases (O' Sullivan et al., 2020). For example, the points of entertainment in a town could bring about a change in health status (S to I) to many individuals, as they attract agents closest to them and beyond. Evidently, the concepts of centrality, accessibility and distance play an increasingly important role in such a "spatial" SIR model.

In this work, we use the SIR general epidemiological framework, yet we couple this with a spatial ABM of human mobility with a town. The elements of the SIR model are integrated in a spatial context, calculating transitions between the SIR states per person and not for the whole population. More specifically, for each individual agent, terms β and γ are computed depending on agent "coexistence" in the same space (school, home, entertainment, etc.). The particular mobility ABM of the coupled model represents an effort to circumvent the need for detailed individual data, and rather utilizes general knowledge on recurring patterns of mobility/activity within a week (home, work, shopping, etc.). Coupling the ABM with the SIR model allows the evaluation of alternative mobility restrictions in the context of the COVID-19 pandemic.

4 Case study

We used the coupled SIR/ABM to generate a set of simulations of individual trajectories and associated contacts and possible COVID-19 infections in a virtual town (see Figure 2) with a population of 4000 individuals, a typical town size in Southern Europe. The time horizon of the simulation was 180 days; initially only 5 people were infected with the COVID19 virus. We also used a period of 4 to 7 days for disease incubation and R0=3 as an expected number of close contacts to be infected from an infected individual.

Intervention scenarios

We employed the coupled ABM to investigate the effects of different types of policy interventions, examining the effects they may have on the course of the spread of an infectious disease. The interventions we introduced in our ABM indirectly affect mainly the value β of the above SIR model by changing the rate at which people are infected.
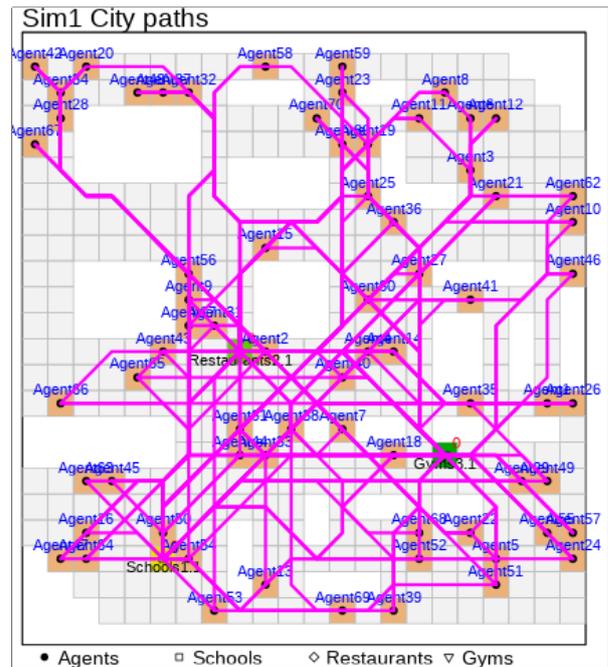
Figure 2. Synthetic town layout with points of interest, and example of simulated agent locations.

More specifically, term β in our model is affected by:
- How many contacts does each agent have per day (Intervention 1)
- For each of its infected contacts, what is the probability of being infected (Intervention 2)

Regarding term γ, we used a commonly accepted value which however has not yet been fully documented since the COVID-19 pandemic is still evolving. The value for term γ in our spatial model is $\gamma = 5\%$, meaning that for each time step of the model 5% of the infected population is removed/recovered. At this stage, we do not include deaths or different age groups in the ABM for simplicity.

The following interventions were implemented and the results were evaluated either individually or comparatively:

Intervention 1: Different types of lockdown:

1. no restrictions (20 daily contacts on average per agent)
2. entertainment restriction: (10 daily contacts on average per agent)
3. entertainment + school restrictions: (5 daily contacts on average per agent)
4. entertainment restrictions + school + "stay home" campaign: (2 daily contacts on average per agent)

Intervention 2: Use of personal hygiene measures:

1. no measures (5% chance of infection on each contact on average)
2. antiseptic use (4% chance of infection on each contact on average)
3. antiseptic use + mask (3% chance of infection on each contact on average)

1000 simulations were performed for each of the 12 combinations (3 * 4) of interventions and the average of each combination was computed. Figure 3 provides the results for each combination of measures in the virtual town.
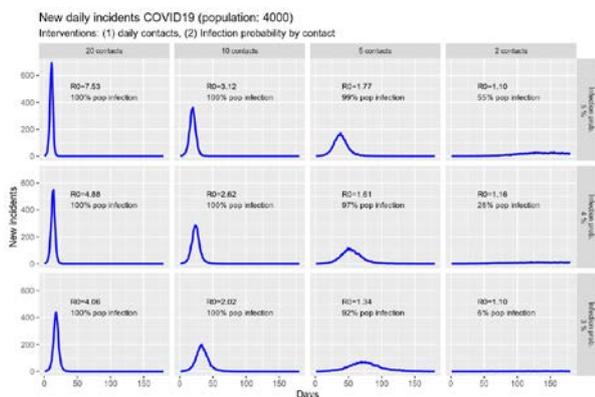
Figure 3. Results based on 1000 simulations. New daily incidents for the 12 combinations of interventions.

As shown in Figure 3, during the first days, i.e., without lockdown restrictions and with entertainment restrictions, the daily new cases are as many as the individual contacts. The overall development of new cases is gradually decreasing as restrictive lockdown measures are applied (fun, school, "we stay home"). Also, the use of personal hygiene measures intensifies this reduction even more, to the point where in some cases only 2% of the population was infected after 10 days.
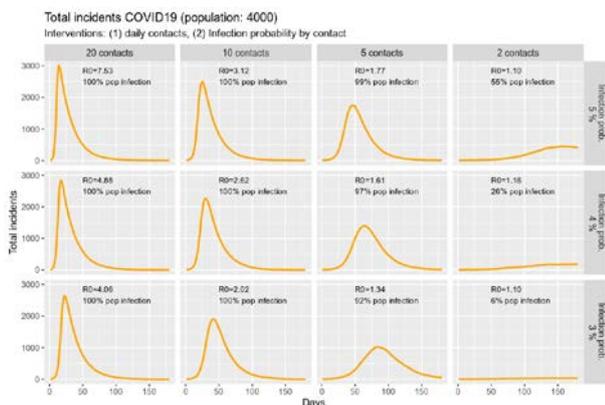
Figure 4. Total incidents for the 12 combinations of interventions.

Figure 4 depicts the temporal distribution of total cases in this virtual town. This graph shows the overall health status of the town and reflects the extent of the disease spread to ABM model agents. It appears that during the first days, the number of total cases in the town increases. However, this increase is somewhat limited if restrictive lockdown measures are implemented to reduce the daily contacts of agents. The effect of lockdowns is very obvious even without any personal hygiene measures (first row of graphs). In this case, as long as lockdown restrictions (from left to right, in the first row) are applied, the total number of people affected by the COVID-19 is gradually reduced from 100% down to 63%.

Figure 5 shows a comparative superposition graph for the 12 scenarios. Here, the impact on the overall cases of the city by type of intervention is evident. The flattened shape of the curves is clear as lockdown measures and personal hygiene measures increase.
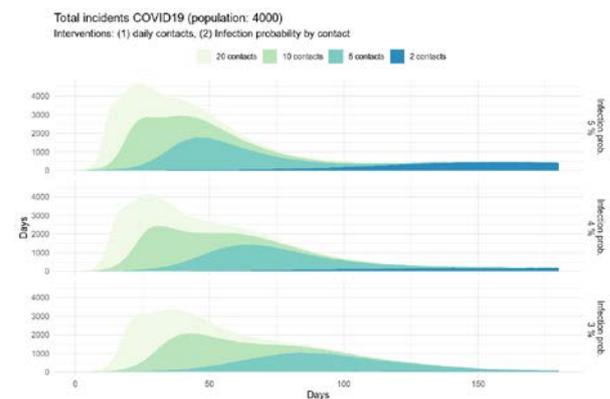
Figure 5. Comparison of the 12 combinations of interventions in terms of total daily cases.

5 Discussion

The COVID-19 pandemic demonstrated that a well informed policy design is vital for formulating and implementing effective interventions to limit virus spread (Hsiang et al., 2020). In this context, ABMs are considered as an appropriate tool for modelling human activity (mobility and contacts) within a pandemic context, taking into account several parameters (virus transmission rate, city/community-level dispersion, population and its spatial distribution, etc.), on which policy-makers could rely to take effective measures against disease spread.

ABMs can significantly reduce government response time for decision-making, as through the creation and evaluation of different modelling scenarios it can better

be determined whether restrictive measures , such as quarantine, mandatory use of masks and/or curfew, could act beneficially towards the alleviation of the epidemic load in a study area. Furthermore, the gradual lifting of any imposed restrictive measures, along with a reassessment of the pandemic state, may also be evaluated through the use of ABMs.

The ABM implemented in this work utilizes general knowledge on recurring patterns of human mobility within a week (going to home, work, shopping, etc.) to evaluate alternative mobility restrictions in the context of COVID-19 spread. A possible future extension could pertain to the introduction of different probabilities of infection per age group to reflect different health conditions among sectors of the population. The model could be also extended in the future by adding more complex types of measures and interventions, which could be analysed as "what-if" scenarios not only in terms of their implementation but also in the context of their removal or lifting.

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