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Conference Paper · December 2020

DOI: 10.1109/SCCC51225.2020.9281149

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COVID-19 Transmission During a Tsunami Evacuation in a Lockdown City

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***Abstract*—SARS-CoV-2 is a new and highly contagious virus that has expanded worldwide reaching the most distant places. In March 23rd (2020), the first case of COVID-19 was reported in the city of Iquique, northern Chile. Later, in May 15th authorities declared a city lockdown that has lasted for more than 14 weeks and counting. Using Agent Based Modeling and Simulation, we study the effects on COVID-19 transmission during a tsunami-threat evacuation in the lockdown of the city of Iquique. Five different scenarios were simulated, considering different amounts of infected agents with capacity to spread the disease, different distribution of agents across the city and two different rates of contagion among agents. Results showed that most contagions occur within the first 15 minutes of the evacuation, while agents are fleeing to the safe zone. The effect on transmission rates resulted highly dependent on the spatial distribution of infected population.**

***Index Terms*—COVID-19, Agent-Based Simulation, Evacuation, Tsunami, City Lockdown**

I. Introduction

SARS-CoV-2 (COVID-19) is a rather new kind of Coronavirus [1]. It is a highly contagious viral disease that has spread worldwide in less than 4 months, quickly becoming a major health threat. It was first discovered in Wuhan, China in December (2019) [2], and the first case outside China was confirmed in Thailand [3]. According to data reported by the COVID-19 Dashboard by the Center for Systems Science and Engineering at Johns Hopkins University [4], as of August 31st (2020), there were more than 25 million cases globally and over 846.985 deaths caused by the virus. Authorities in each country have taken different measures in an attempt to control contagions, some with more success than others. Airborne transmission (in indoor as well as outdoor spaces) [5]–[8] is one the most accepted modes of COVID-19 contagion. Thus, among the main methods to prevent the spread of COVID-19 is social distancing and wearing face masks [9].

Computer simulations are proven to be a powerful tool, and are considered of paramount importance in the development of strategies to tackle the spread of contagious diseases. Most simulation models to study contagion disease transmission are based on: i) Cellular Automata (CA), ii) Ordinary Differential Equations (ODE) or iii) Agent-Based Simulations.

ODE models simulate disease transmission focusing in the spread of the disease considering a homogeneous population [10], most of them through an epidemiological SEIR approach and its several variations [11], [12]. Agent-based simulations allow to model disease contagion as an emerging effect of individual agent behavior interaction with other agents and/or with its environment [13]. On the other hand, CA permit to model the population as a whole but focusing in subsets of the population, in a discrete fashion.

Many models about epidemic disease contagions have been developed so far [10], [11], [14]–[16], however, few have considered the case where natural catastrophes strike during the occurrence of a pandemic disease like COVID-19.

In this paper, we address such a problem, by focusing on population individual behavior during a city-wide evacuation – due to a tsunami threat – in a city lockdown because of the COVID-19 pandemic. Using agent-based simulation (ABS) we study the effects on the disease transmission among individuals of the city's population. Our case of study takes place in Iquique (northern Chile).

The rest of this paper is organized as follows. In section II we will provide some background information about the city of Iquique, with its always-present tsunami risk and current COVID-19 cases, about ABS and the epidemiological model SEIR. In section III we review related works about ABS and its applications in emergency evacuations and infectious disease transmission. Also, we discuss COVID-19 epidemiological models in outdoor scenarios. Later, in section IV, we formally define our proposed ABS model for city-wide evacuation scenarios. Section V presents our case of study and the obtained experimental results. Finally, in section VI, we present the conclusions about this work and the possibilities it pose for future work.

We provide reproducible simulation models available in our GitHub repository [17]. Also, videos of the simulated evacuation scenarios are available in YouTube [18].

II. Background

A. Iquique

Iquique is a coastal city located in northern Chile. It is set on a platform sitting on the rim of the so-called “Pacific Fire Ring”, and is surrounded by the Pacific Ocean and the cliffs of the Coast Mountain range. Because of its location and topology, Iquique has a high risk of being flooded in the event of a tsunami. Government authorities are frequently trained to quickly respond to such events, and evacuation drills – involving the population – are realized in (almost) a yearly basis. In the event of a tsunami alert, people located in the flooding risk area (between the coast and the security zone) must quickly evacuate to the security zone (depicted as a green line in Figure 1).

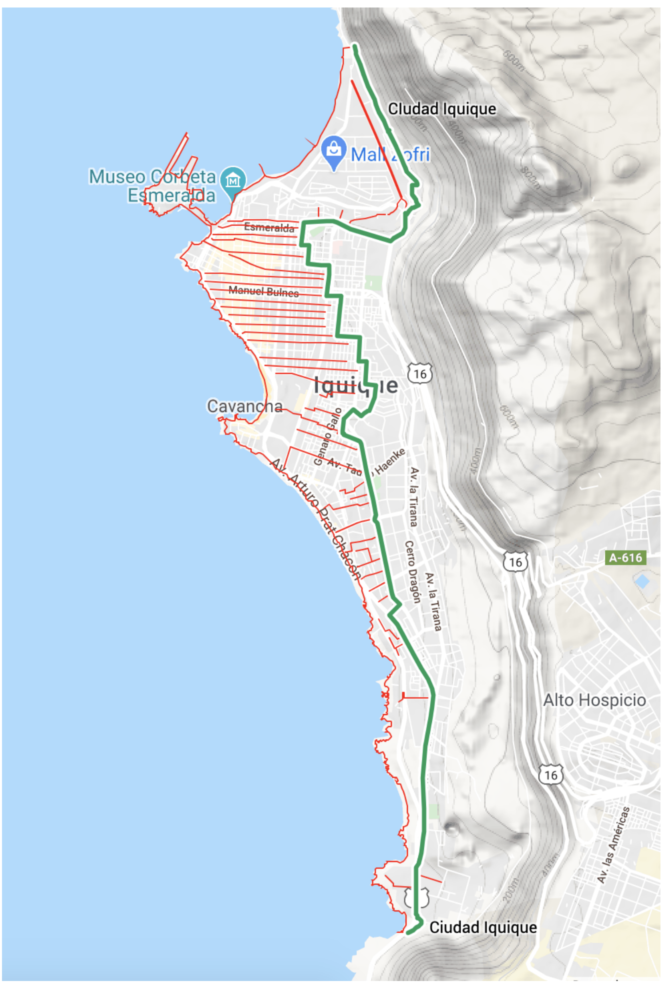


Fig. 1: Tsunami evacuation map of Iquique – Main evacuation routes are depicted as red lines, and the security zone marked by green line – based on [19].

According to the Chilean census of 2017 [20] Iquique has a population of 191.468 inhabitants. With the help of a GIS software, combining census information and the ONEMI tsunami flooding risk map, it was estimated that the population that live in the risk zone of Iquique reaches a total of 99.193 inhabitants.

The first case of COVID-19 reported in Chile occurred in March 3^{rd}, but in Iquique the first case is reported in march 23^{rd}. The natural isolation of cities in northern Chile, mostly placed in the coast surrounded by the Atacama desert, was the main factor to this late begin. However, once the pandemic arrived to these cities, it spread rapidly (see Figure 2). The nearest cities to Iquique, Arica (310km) and Antofagasta (416km), started the lockdown before than Iquique (April 17th and May 6th, respectively). In the middle of social unhappiness by, in the judgment of the citizens, a slow reaction of their authorities, the number of contagions in the Tarapacá region grew up to 779 cases (440 cases in Iquique), with 425 active cases (293 cases in Iquique) and 2 deaths before the city lockdown was declared (May 16th), in a region with only one hospital and 15 ICU beds (at the beginning of pandemic) to treat a population of 330.558 people.

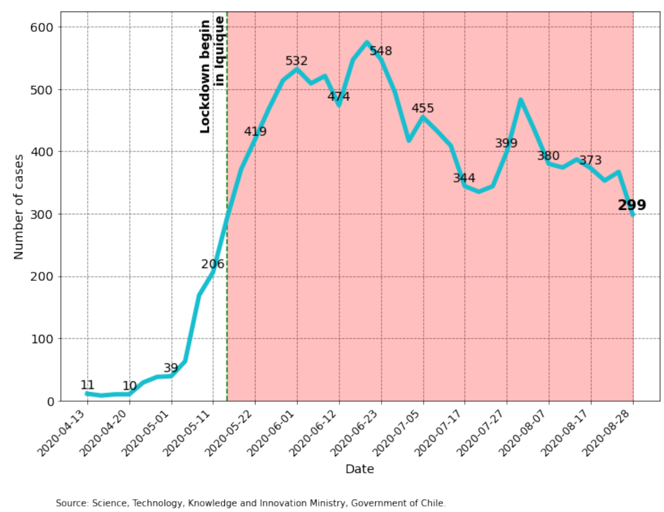


Fig. 2: Number of active cases reported in Iquique between April 13th and August 28th (Source: Science, Technology, Knowledge and Innovation Ministry, Government of Chile.).

B. Agent-based Modeling and Simulation

Agent-based simulation corresponds to an individual oriented modeling (IOM) technique suitable to simulate autonomous entities [21]. Agents are described by their own state variables and rules of behavior, they may be located in an environment – formed by a uniform n-dimensional lattice – where they can move and interact (in the form of cooperation or competition) with other agents and/or the environment.

Agents are programmed to react according to a set of predefined rules, that – based on the modeler needs – may range from simple binary or stochastic decisions up to highly detailed complex behaviors [22], [23]. These rules govern individual agents behavior, and can be defined in relation to other agents and/or to their environment.

ABS are step-driven, meaning that the state of each agent and the environment evolve in discrete time steps. At each step,

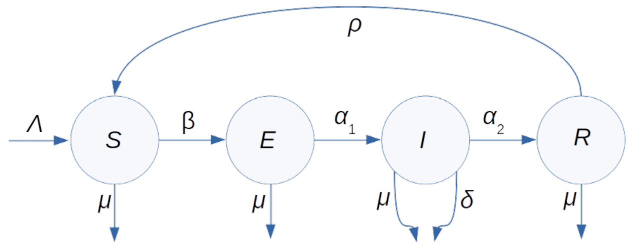


Fig. 3: Transition state diagram for SEIR model.

the rules of every agent are evaluated and its state variables are updated in a synchronous manner.

An ABS model is able to describe the emergent behavior of a real-life system derived solely from the interactions among its agents [24].

Due to this characteristics, ABS models have long proven to be useful for modeling spatially explicit models such as individuals interaction social dynamics [25], emergency evacuations [26], [27] and infectious disease transmission and mitigation strategies [14], [28]–[31].

C. SEIR Models

In a SEIR model, population is divided into four classes, namely: Susceptible (S, those able to to contract the disease), Exposed (E, those who have been infected, but not yet infectious and possibly asymptomatic), Infectious (I, those able to transmit the disease) and Recovered (R, those who have recovered and become immune). Their dynamics is described by the graph in Figure 3. The nodes (labeled S, E, I and R) represent the class where each person can be in. The arcs are labeled with the functions associated to the change from one stage to another. They can be summarized as:

Λ: Increase rate of population.
β: Exposing rate.
α_1: Morbidity COVID-19 rate.
α_2: Recovery COVID-19 rate.
ρ: Immunity loss rate.
μ: Mortality rate by other causes than COVID-19.
δ: Mortality rate by COVID-19.

As in earlier works about SEIRS [32], [33], considering this system in function of time, t, an ordinary differential equations (ODE) can be derived:

$$\begin{aligned} \frac{dS}{dt} &= \Lambda + \rho - \beta - \mu \\ \frac{dE}{dt} &= \beta - \alpha_1 - \mu \\ \frac{dI}{dt} &= \alpha_1 - \alpha_2 - \mu - \delta \\ \frac{dR}{dt} &= \alpha_2 - \rho - \mu \end{aligned} \tag{1}$$

With the initial conditions: $S(0) = S_0$, $E(0) = E_0$, $I(0) = I_0$ and $R(0) = R_0$.

Since dynamics of the modeled situation (a city-wide evacuation) happens in less than one hour timescale, our rate of interest during the simulated event is β, since the remaining: α_1, α_2, ρ and δ, change in a greater timescale, and Λ and μ don't depend on the illness evolution.

III. Related Work

In this section, we discuss the use of ABS to model emergency evacuations and epidemic disease transmission. Also, we review research work about outdoors COVID-19 transmission.

A. Agent Based Models

1) Emergency Evacuations: Emergency evacuations imply the rapid displacement of part of a population from a place under threat to a safe zone. Most efforts for large scale city-wide evacuations simulations have been done using Cellular Automata approaches [15] due to its ability to represent aggregated population with few computational resources. In this sense, Cell-DEVS (a simulation formalism that implement the concept of CA) has been extensively used to model crowd evacuations [34], [35]. Most ABS evacuation models are focused in the evacuation of indoor spaces [36]. To the best of our knowledge, there are only few evacuation research – using ABS – that assume a large population [37]. The work in [38] present a flooding risk management simulator in the city of Towyn (North Whales), the tool consider individuals daily patterns of mobility as well as a flooding model of the city and was validated using information of the 1990 flooding. The simulations performed in this work consider a population of barely 90.000 individuals.

2) Epidemic Disease Transmission: Epidemiology is an important area of study that uses ABS. Many researches uses it as a tool for simulating and studying outbreaks of epidemic diseases and mitigation strategies. Proven to be a powerful tool, ABS has been used to model contagious diseases [39] – such as the Influenza virus – spread in urban areas [40]. Authors in [41] proposed a multi-agent model to simulate H1N1 influenza contagions in Egypt. They adapted a SIR model in order to describe different kinds of agents. Data from the 2006 Egyptian Census was analyzed to determine simulation parameters such as population distribution and also social relations (e.g., sibling, child, other families, coworker, etc.) were considered. The developed model allowed the authors to predict infections peaks and mortality rates for different scenarios. The work in [14] presents an artificial town with a population just 1.500 agents. The authors focused their study in modeling the propagation of a viral disease in a place were agents are densely connected, such as the public transportation system. Experiments were performed exploring different control strategies: from individuals personal protection measures and closing of gathering places to epidemic control surveillance, showing that prevention measures are effective. In both studies, there was a small amount of simulated agents. Authors in [30] developed an ABS model and concluded that mitigation strategies (such as school closure and travel restrictions) help to delay the spread of an influenza pandemic in the U.S considering a population of 281 million individuals. An ABS model to study COVID-19 risks of transmission in indoor spaces is proposed in [13]. The model present simple rules to describe the contagions dynamic among agents and also to describe their displacement within the environment.

the proposed rules are based on simple probabilities to define their activation. In [42] authors developed a fine-grained ABS model calibrated to reproduce the main transmission characteristics of COVID-19 in Australia, used to compare different contention strategies. As can be inferred, most research on epidemic disease transmission ignore population mobility patterns and/or the geographic demographic distribution. An exception would be the work of [31], that present a large-scale model to study seasonal influenza outbreaks in Zurich, Switzerland. In order to have a realistic approach to COVID-19 transmission dynamics we considered an epidemiological model SEIR in our ABS model.

B. *COVID-19 Outdoors Transmission*

Despite the lack of knowledge on details about COVID-19 transmission, the main reported mechanisms – which are common to respiratory diseases – are in the form of aerosols, emitted by infected persons when coughing or sneezing. These airborne droplets can be directly inhaled or touched from surfaces where they have been deposited, by exposed receptors ([5], [7], [43], [44]). For the exposure due to the evacuation event simulated in this article, the relevant mechanism is related with the close-range aerosol transmission. This have been observed in about 6 feet (1.8 meters) close to the "source" [44]. However, punctual sneezing or coughing events would deserve a modeling based on real measurements with a local dispersion pattern.

Due to the relative stability and calm near the ground level – common in northern and central Chile by the influence of the South Pacific High – which means stable atmospheric conditions, quite similar to closed spaces, being marginal the main factors considered in dispersion models [45] specially in short time periods, we consider the rate of transmission to a susceptible person, S, in function of the number of infected persons, I, near him or her within a given radius r. We have considered for r a "social distance" of 1.8 meters [9] in despite of reported 7.5 meters [7], considered the maximum span of a cloud of droplets around a sneezing or coughing person. This could be expressed in an extra rule, in further works.

IV. Proposed Agent-Based Evacuation and Contagion Model

In this section we present our spatially explicit ABS model for disease contagion during a city-wide evacuation.

A. *Model Description*

The purpose of this work is to study the effects of a city-wide evacuation – during a lockdown – on COVID-19 transmission. As the evacuation takes place, it would be common for the evacuees to ignore – or at least not to completely fulfill – contagion prevention measures such as: social distancing and wearing face masks among others. Also, we consider the fact that it would be difficult for the evacuees to maintain social distancing once they reach the security zone.

Based on the ideas of the SEIR model [11], our simulation considers four different kind of agents, described in Table I.

TABLE I: COVID-19 Infection Stages for Agents.

Stage	Name	Description
$s\prime$	Susceptible	The individual is not infected by COVID-19.
$e\prime$	Exposed	An individual that has been infected with COVID-19 but is in the incubation stage, presents no risk to infect other persons.
$i\prime$	Infectious	An individual that has finished the incubation period and may infect other people, may or may not present symptoms.
$r\prime$	Recovered	The individual was infected by the disease, survived and is no longer infectious. It has developed a natural immunity to the virus.

It is worth to mention that there are variations of the SEIR model (such as [16]) that consider more stages of the disease, in which a person may take several days to transit from one stage to the next. However, since our simulations focus in a short time span, there are no transitions among stages, so they can be obviated.

The proposed model is formally defined as:

$$M =< A, C, R, T >$$

Where:

A is the set of agents a, with $a = \{(a_c, a_p) | a_c \in C, a_p \in P\}$.

$C = \{s\prime, e\prime, i\prime, r\prime\}$ is the set of COVID-19 infection stages (as described in Table I).

R is the set of rules to be applied to each agent $a \in A$. Rules are defined over each agent and/or its surrounding environment.

$P \subseteq T$ is the set of geographical locations that are accessible (such as streets/roads) for any agent $a \in A$.

T is the territory or environment space, a set of geographical locations within the limits of the city of Iquique.

The distinction among P and T is made because, initially, agents are located within their homes (represented by city blocks within the territory), but once the evacuation starts they only move along the streets/roads, P, in direction to the security zone.

Since our proposal consider that agents belong to different COVID-19 infection stages, we also define the following disjoint subsets of A:

$S \subseteq A$ where $\{a = s,\ s \in S \mid a_c = s\prime\}$ is the set of *susceptible agents*.

$E \subseteq A$ where $\{a = e,\ e \in E \mid a_c = e\prime\}$ is the set of *exposed agents*.

$I \subseteq A$ where $\{a = i,\ i \in I \mid a_c = i\prime\}$ is the set of *infected agents*.

$R \subseteq A$ where $\{a = r,\ r \in R \mid a_c = r\prime\}$ is the set of *recovered agents*.

B. *Model Rules*

In ABS, a set of rules is defined in order to model the behavior of individual agents. These rules allow agents to change their state, to move, and to interact with its environment and/or with other agents.

In this model, the set of rules is defined in order to model the agents displacement during the city evacuation and, also, to model COVID-19 contagion among individuals:

1) Contagion Rule: This rule permit to model the transmission of COVID-19 from infected individuals to susceptible persons. For our model, we have assumed an exposing rate for a susceptible person, s, distributed according the number N_I of infected ones (i) within a circle around s, distributes according the probability distribution function f, given by the additive rule for independent probabilities:

$$\sum_{i_1=1}^{N_I} p_{i_1} + \sum_{\substack{i_1=1 \\ i_2=i_1+1}}^{\substack{N_I \\ N_I-1}} p_{i_1} p_{i_2} + ... + (-1)^{N_I-1} p_1 p_2 p_3 ... p_{N_I} \quad (2)$$

where p_k $(k \in \{1, ..., N_I\})$ correspond to the probability of transmit COVID-19 to the k-esime infected individual near s, at 1.8 meters or less.

By the other hand, each susceptible person, $s \in S$, will have a probability of developing the illness, p_D according the contact with infected ones. Assuming independence between this p_D, depending on his or her immunity and also on which measurements this person adopt, such as mask wearing, keeping a social distance, etc. Since this category isn't immune, p_D value will be uniformly distributed between 0.2 and 0.9.

2) Evacuation Rule: This rule is defined to represent agents walking towards the security zone during an evacuation. It is worth to mention that according to Chilean government authorities in charge during natural disasters (ONEMI), in the event of a city evacuation procedure due to a tsunami threat, the use of vehicles is forbidden in urban areas [46].

Therefore, this rule, force each agent to move to a new place in P, following a (previously) computed route towards a target point $P\prime$ located in the security zone of the city (as shown in Figure 1).

V. Experimental Results

In this section, we present three evacuation simulation scenarios taking place in Iquique during the city lockdown, modeled using the Gama Simulator [47]. Here, we focus on the effects of COVID-19 contagions attributed to a city-wide evacuation.

The model is preset according to official information (when possible) about Iquique and COVID-19. For each simulation, the territory and its streets/roads corresponds to the city of Iquique. The security line is set according to recommendations of ONEMI (as observed in Figure 1) [19]. A total of 99.193 individual agents are considered in the simulations, being that the estimated population that live in the tsunami flooding risk zone of Iquique. The initial geographic distribution of the agents in the city is defined according to [20]. Finally, The walking speed of agents during evacuation is attributed uniformly in the range 0.88 – 1.45 meters per second according [26], [48].

We consider 5 simulation experiments grouped into 3 scenarios. Scenario A corresponds to official reports figures as of August 28th (2020), whereas scenarios B and C corresponds to the lowest and greatest amounts of COVID-19 active cases during the lockdown up to date. For experiments A, B and C, the amount of infected agents corresponds to an estimation of official reports [49] in a direct proportion to the population that live in the flooding risk zone (I_0, in terms of the initial conditions associated to the ODE). The geographical distribution of infected agents (i.e., active COVID-19 cases) in scenario A was made according to reports of IDE Chile [50]. In scenarios B and C, infected agents are mainly distributed in downtown (most densely populated area) and in the southern suburb of the city (least densely populated), as described in Table II.

TABLE II: Simulated Scenarios

Scenario		**Infected Agents (reported)**	**Infected Agents (estimated**)**	**Distribution of Infected Agents**	**Recovered Agents (estimated**)**
A	1	367	264	As officially reported*	4.049
B	2	293	211	80% Downtown – 20% Suburb	147
	3	293	211	50% Downtown – 50% Suburb	147
B	4	575	414	80% Downtown – 20% Suburb	1623
	5	575	414	50% Downtown – 50% Suburb	1623

*Reported in August 28^{th}, 2020 [50].
**Estimated values derived from regional data.

Figure 4, describes the process in which an infected (I) individual transmits CODIV-19 to a susceptible one. In Figure 4(a), both a susceptible (S) agent and an infected agent are following the evacuation path towards the security zone at a safe distance from each other. Next, in Figure 4(b), the infected agent invades the safe space of the susceptible agent, the probability of S acquiring the disease from I is evaluated. Then, in Figure 4(c), the probability of contagion stated that the susceptible agent acquires the disease, being transformed into an exposed (E) agent. Finally, in Figure 4(d), both agents continue walking to the security zone.

In Figure 5, it can be observed a visualization of the progress of the simulation. Figure 5(a), shows agents at the beginning the evacuation, fleeing to the security zone. Figure 5(b), shows the evacuation simulation after 12:36 minutes, where most agents (depicted as black dots) have reached the security zone.

A. Current Case

The scenario for this simulation is set to have occurred in August 28th, 2020. At this date, the current amount of COVID-19 active cases in Iquique is 367, however, only 264 of them live in the tsunami flooding zone. Thus, this simulation consider 264 infected agents and 98.929 susceptible/exposed,

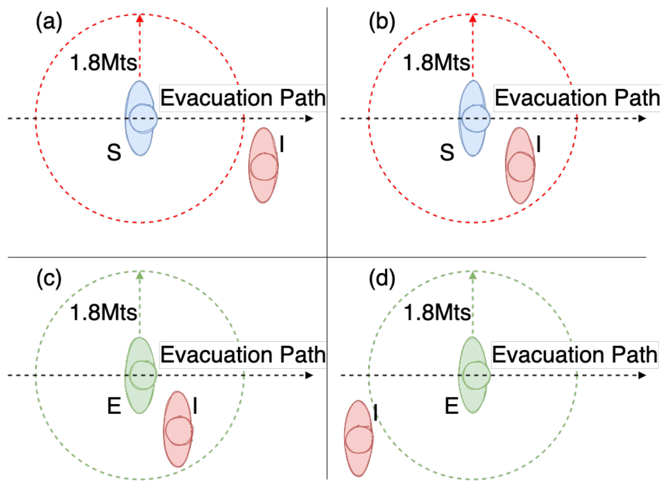
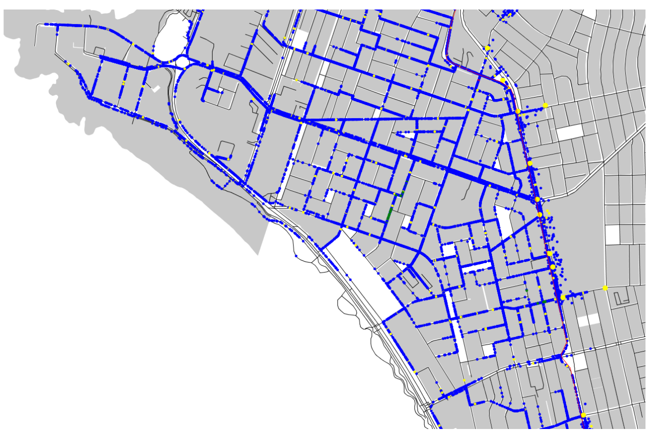
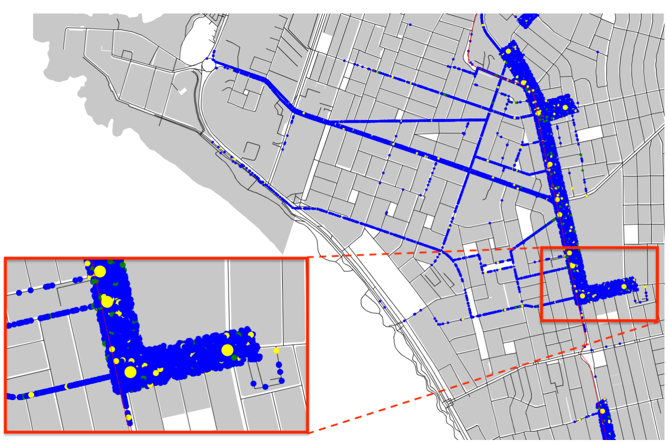


Fig. 4: Process of a susceptible agent acquiring COVID-19 and being transformed into an exposed agent.



(a) Simulated evacuation (minute 2:16)



(b) Simulated evacuation (minute 12:36)

Fig. 5: Visualization of the evacuation simulation in the Playa Brava district.

considering 4049 of them as recovered agents. The geographical distribution of infected agents was configured according to official reports [50].

B. *Fewer Active Cases*

This scenario is based on figures reported in May 15th (2020), the day before the beginning of the city lockdown. On that day, one of the lowest amounts of active cases was reported ever since the lockdown started. The simulated population sums 99.193 agents, and includes the amount of infected agents in the tsunami flooding zone (211), and an estimation of the recovered agents (147).

C. *Highest Active Cases*

This scenario considers reported information for June 19th (2020), the day with the highest amount of active cases reported so far in the city of Iquique, even during the city lockdown. The scenario simulates a population of 99.193 agents, including an amount of 414 estimated infected agents located in the tsunami flooding zone, and an estimated of 1.623 recovered agents.

D. *Results*

The proposed model is flexible enough to permit the testing of several different hypothesis, considering situations that are impossible to test in real-life conditions. The probability of contracting the COVID-19 for each susceptible individual p_D, as defined in the contagion rule, has been assigned uniformly distributed between 0.2 and 0.9. Regarding probability of transmitting COVID-19, associated to infected ones, two configurations for the contagion rule have been considered. A first configuration, of "higher rate" (HR), consider a uniform probability in the range 0.2–0.9. A second configuration of "lower rate" (LR), more conservative, consider the range 0.2–0.6.

Figure 6, shows how the most of a stable number of transmission of COVID-19 happens within the first 15 minutes (900 seconds, dotted vertical line), when near an 85% of the final stable values are reached. This trend is consistently observed, during the trip to the safe zone, having the most of the transmissions in the early minutes. As could be expected, the greatest increase of exposed population coincides with the maximum number of infected cases, at June 19th –414 cases within the area– (red lines), having a 10% of difference according the geographical distribution of the infected ones, reaching 8140 when a half of them are in the central part of the city and the other ones, within the South sector. Near 1000 less new exposed ones result, if infected population concentrates in the central sector (80% of them).

While becomes clear that the spatial distribution of the infected population is relevant for the spreading of COVID-19, their amount, at least within the observed levels, can't predict by itself, an increase of exposed cases. Considering the beginning of this lockdown –May 15th–, having the minimum infected cases (211), the simulations of these conditions (in

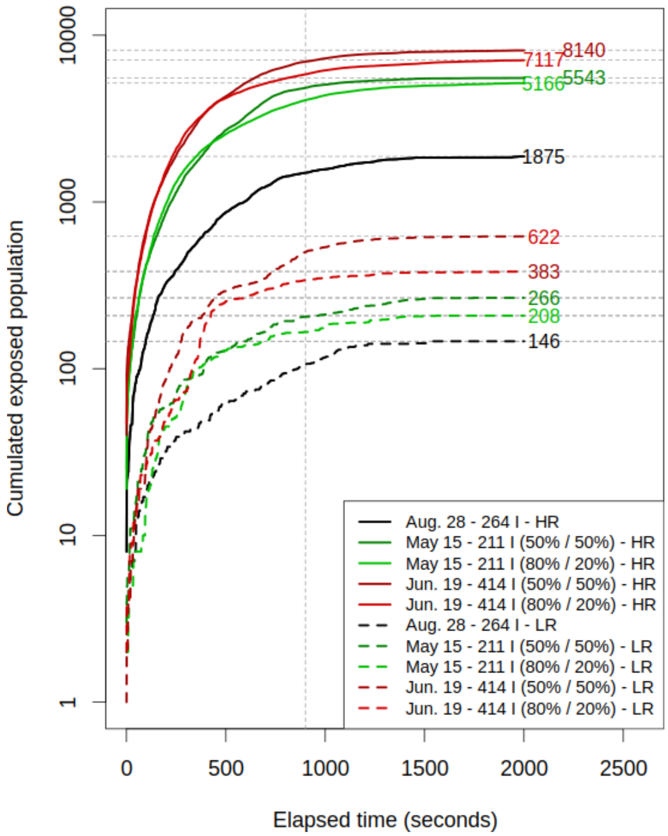


Fig. 6: Simulated increase of exposed population – during a city-wide evacuation of Iquique – in several configurations for: date – spatial distribution of infected population – contagion probability.

green), reached over 5000 new exposed cases, more than twice than results for Aug. 28th.

These results were under HR (0.2–0.9 probability of transmission) assigned to infected people. Considering LR (0.2–0.6), the new exposed cases are one order of magnitude below. Interestingly, they show the same order than HR simulations, being the lowest increase with the Aug. 28th data. The spatial distribution of infected populations, shows a relative greater effect: Roughly 60% for Jun. 19th and 80% for May 15th.

In order to better understand the spatial distribution of the infected population effect, simulations were performed considering the 264 infected ones, reported for Aug. 28th (not plotted) with similar distributions of simulations for the other dates, reaching the final new exposed cases as summarized in III. These values remain below the outcomes for Jun. 19th but over the May 15th. This reinforces the observed effect of the spatial distribution of infected population.

VI. Conclusions

In this work, we proposed an ABS model of a city-wide evacuation due to a tsunami threat. As a case of study, we situated the evacuation in the city of Iquique during the COVID-19 lockdown.

TABLE III: Simulated results for scenario A, considering different geographical distribution of infected agents.

Distribution of Infected Agents	Resulting Exposed Agents
As officially reported*	1875
80% Downtown – 20% Suburb	4099
50% Downtown – 50% Suburb	5844

*Reported in August 28^{th}, 2020 [50].

The proposal was evaluated considering different probabilities of contagion and using real amounts of active cases corresponding to actual dates throughout the lockdown of Iquique. Results showed the catastrophic effects in new COVID-19 infections that can derive from a city-wide evacuation event – that lasts less than an hour – spreading the illness even in the most conservative scenarios in 15 minutes or less. Most new contagions were observed while individuals were fleeing to the security zone, that is during the first 15 minutes (85%). Simulations highlighted the effects on disease spread produced by the spatial distribution of infected agents during a city evacuation. Results showed that simulations in which COVID-19 active cases were more uniformly distributed across the city generated between 7% to 14% more new contagions for the case of a higher rate of contagions, and about 27% to 54% more with a lower rate of contagions.

While the spatial distribution population have consistently shown a relevant effect of the contagion rates, other factors should be further investigated and calibrated to better characterize this phenomenon, including not only infected cases, but also recovered ones.

An unconsidered problem faced during the development of this research, has been the lack of consistent and precise official information regarding COVID-19 cases in Chile and of the Tarapacá region, making this a troublesome task. In an attempt to tackle this problem, simple linear and naive estimations were made. Most official data is available with a granularity to a regional level. This reinforces the capital value of knowing about the location and contacts of the infected population.

Simulations of the post tsunami scenario and its effects on COVID-19 contagion spread is considered for future work.

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