**Overview**

We used a spatially explicit individual-based model to track a simulated COVID-19 epidemic unfolding in a refugee camp in discrete timesteps that correspond to days. The infection starts in one individual, and is transmitted probabilistically among individuals as they interact during daily activities. We modelled epidemics with no interventions, and epidemics where interventions or combinations of interventions are used to reduce disease transmission. We compared the peak number of infected individuals, the time to peak infection, and the total number of individuals infected, with or without interventions.

The parameters that describe the population and the camp simulate the Moria refugee camp on Lesbos, Greece. The parameters that describe disease progression and transmission are drawn from the literature. The parameters that describe individuals’ movements about the camp are heuristic, but our qualitative predictions hold under other reasonable sets of parameter values (supplementary tables S#-##).

Throughout this appendix, we use “Moria” to refer the Moria refugee camp, and “camp” to refer to the camp in our model. We use “person” or “people” to refer to the residents of Moria, and we use “individuals” to refer to individuals in the model population.

**The population**

The model population is comprised of 18,700 individuals. Each individual is characterised by its age, sex, condition, and disease state. Condition describes whether an individual is healthy or has a pre-existing condition that increases the risk of severe infection or mortality from COVID-19 (i.e., ). Each individual is assigned an age, sex and condition that matches a randomly selected person from the medical records of the Moria camp. These do not change over time. Disease state describes the progression of a COVID-19 infection in an individual, and thus changes over time. The initial disease state for all individuals is “susceptible.”

**The camp**

Each individual is a member of a household that occupies either an isobox or a tent. Isoboxes are prefabricated housing units with a mean occupancy of 10 individuals. Tents have a mean occupancy of 4 individuals. A total of 8,100 individuals occupy isoboxes and 10,600 individuals occupy tents. The exact occupancy of each isobox or tent is drawn from a Poisson distribution, and individuals are assigned to isoboxes or tents randomly without regard to sex or age. This is appropriate because many people arrive at Moria travelling alone, and thus isoboxes or tents may not represent family units.

The entire camp covers a 1 x 1 (e.g., km) square. Isoboxes are assigned to random locations in a central square that covers one half of the area of the camp. Tents are assigned to random locations in the camp outside of the central square. There are 144 toilets evenly distributed throughout the camp. Toilets are placed at the centres of the squares that form a 12 x 12 grid covering the camp. The camp has one food line. The position of the food line is not explicitly modelled.

In Moria, the homes of people with the same ethnic or national background are spatially clustered, and people interact more frequently with others from the same background as themselves. To simulate ethnicities or nationalities in our camp, we assigned each household to one of eight “backgrounds” in proportion to the self-reported national origins of people in the Moria medical records. For each of the eight simulated backgrounds, we randomly selected one tent or isobox to be the seed for the cluster. We assigned the *x* nearest unassigned households to that background, where *x* is the number of households in the background. Thus, the first background occupies an area that is roughly circular, but other backgrounds may occupy crescents or less regular shapes.

**Disease Progression**

If an individual becomes infected, the infection progresses through a series of disease states (figure S#). The time from exposure until symptoms appear (*i.e*., the incubation period) is drawn from a Weibull distribution with a mean of 6.4 days and a standard deviation of 2.3 days [1]. In the first half of this period, the individual is “exposed” but not infectious. In the second half, the individual is “pre-symptomatic” and infectious [2]. Fractional days are rounded to the nearest whole day in discrete-time simulations. After the incubation period, the individual enters one of two states: “symptomatic” or “1st asymptomatic.” Children under the age of 16 become asymptomatic with probability 0.836 [3] and others become asymptomatic with probability 0.178 [4]. Individuals remain in the symptomatic or 1st asymptomatic states for 5 days and are infectious during this period. After 5 days, individuals pass from the symptomatic to the “mild” or “severe” states, with age- and condition-dependent probabilities following Verity and colleagues [5] and Tuite and colleagues [6]. All individuals in the 1st asymptomatic state pass to the “2nd asymptomatic” state. Individuals are infectious in these states. On each day, individuals in the mild or 2nd asymptomatic state pass to the recovered state with probability 0.37 [7], and individuals in the severe state pass to the recovered state with probability 0.071 [8]. Recovered individuals are not infectious, and are not susceptible to reinfection. We do not model deaths explicitly, but this is unlikely to affect the dynamics of the epidemic if neither recovered nor dead individuals are infectious.

**Infection Dynamics**

Infection can be transmitted from infectious to susceptible individuals as they go about their daily activities. Let *pidw* denote the probability that susceptible individual *i* becomes infected on day *d* by transmission route *w*, where indicates transmission within the household, at toilets, in the food line, or as individuals move about the camp, respectively. The probability that susceptible individual *i* becomes infected on day *d* is then

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|  | (1) |

We lack detailed information on how people use space in Moria or any other refugee camp. Therefore, we do not model movement explicitly, but instead calculate the *pidw*s for each individual given its expected activities on each day. This reduces the computational time for simulations.

*Infection within the household*. On each day, each infectious individual infects each susceptible individual in the same household with probability *ph*. Thus, if individual *i* shares a household with *hcid*infectious individuals on day *d*, then

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|  | (2) |

*Infection at toilets*. We assume that every individual visits the toilet nearest its household 3 times per day, and must always wait in line. If a susceptible individual is in front of or behind an infectious individual in the toilet line, the susceptible individual becomes infected with probability *pt*. Thus, the probability that susceptible individual *i* becomes infected in the toilet on day *d* is

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|  | (3) |

where *tcid* and *tid* are the numbers of infectious individuals and of all individuals, respectively, that share a toilet with individual *i* on day *d*.

*Infection in the food line*. The food line forms 3 times per day. We assume that only individuals without symptoms (i.e., susceptible, exposed, pre-symptomatic, asymptomatic, and recovered) attend food lines. Food is delivered to individuals with symptoms by others, without interaction (e.g., food might be left outside homes). Each individual without symptoms attends the food line once per day on 3 out of 4 days. On other occasions, food is brought to that individual by another individual without additional interactions. For example, food might be brought by a member of the same household, or by a neighbour with whom the individual would otherwise interact (see below). If an individual attends the food line, it interacts with two individuals behind it and two individuals in front of it in the line. If a susceptible individual interacts with an infectious individual in the food line, the susceptible individual becomes infected with probability *pf.* Thus, the probability that susceptible individual *i* becomes infected in the food line on day *d* is

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|  | (4) |

where *nyd* is the number of infectious individuals without symptoms (i.e., pre-symptomatic and asymptomatic) in the camp on day *d*, and *nzd* is the total number of individuals without symptoms in the camp on day *d*.

*Infection as individuals move about the camp*. Individuals move about outside their households, and interact with individuals from other households as they move. We assume that each individual occupies a circular home range centred on its household, and uses all parts of its home range equally. Two individuals may interact if their home ranges overlap. If individuals *i* and *j* have home ranges with radii *ri* and *rj*, respectively, and the distance between their households is *dij*, then area of overlap in their home ranges is

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|  | (5) |

The proportion of time that individuals *i* and *j* spend together in the area of overlap is

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|  | (6) |

and the relative encounter rate between individuals *i* and *j* is

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|  | (7) |

Equation (7) ensures that individuals encounter each other more frequently if they co-occupy a smaller area than if they co-occupy a larger area. To obtain the interaction rate between individuals *i* and *j* from the relative encounter rate, we scale by a factor *gij* to account for ethnicity or country of origin. In particular, *gij* = 1 if individuals *i* and *j* have the same background, and *gij* = 0.2 otherwise. Furthermore, we scale the interaction rate such that two individuals with the same background that share an identical home range with a radius of *rs* interact on average once each day. The parameter *rs* allows us to scale the mean interaction rate in the population independent of the distance that people travel around their homes. After scaling, the daily rate of interaction between individuals *i* and *j* is

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|  | (8) |

We assume that only individuals without symptoms interact in their home ranges. Thus, the rate at which individual *i* interacts with infected individuals in its home range on day *d* is

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|  | (9) |

where I(*j,d*) = 1 if individual *j* is pre-symptomatic or asymptomatic on day *d* and I(*j,d*) = 0 otherwise. The summation in equation (9) runs over all individuals in the model that do not share a household with individual *i*. The probability that susceptible individual *i* becomes infected on day *d* while moving about its home range is thus

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|  | (10) |

where *pm* is the probability of transmission when a susceptible individual interacts with an infectious individual.

*Assigning parameter values*. The probabilities that COVID-19 is transmitted among individuals in different settings are not well-understood. Therefore, we studied both high- and low-transmission scenarios. In the high-transmission scenario we set *ph* = 0.33, *pt* = 0.099, *pf* = 0.407, and *pm* = 0.017, and in the low-transmission scenario we set *ph* = 0.0397, *pt* = 0.0067, *pf* = 0.0397, and *pm* = 0.006. These values are derived from the literature [7, 9-11] in supplementary information S2. We also know very little about how people use space or interact in Moria or in other refugee camps. Thus, we modelled high- and low-movement and high- and low interaction scenarios. In the high-movement scenario, we assumed that males over 10 years old use home ranges with radius 0.2 (i.e., 200 m), and that males under 10 years old and all females use home ranges with radius 0.05. In the low movement scenario, we assumed that males over 10 years old use home ranges with radius 0.1, and all others use home ranges with radius 0.02 m. In the high-interaction scenario, we set *rs* so that the average individual in the camp interacts with 20 others per day (i.e., *rs* = 0.0226 and *rs* = 0.0202 in high- the low-movement scenarios, respectively). In the low-interaction scenario, we set *rs* so that the average individual in the camp interacts with 5 others per day (i.e., *rs* = 0.0113 and *rs* = 0.0101 in high- the low-movement scenarios, respectively).

**Interventions**

We modelled four different interventions that might be imposed on the baseline model, alone and in combinations: sectoring, PPE, remove-and-isolate, and lockdown.

*Sectoring*. The camp in our baseline model has a single food line where transmission can occur among individuals from any parts of the camp. This facilitates the rapid spread of infection. A plausible intervention would be to divide the camp into sectors with separate food lines, and require individuals to use the food line closest to their households. To simulate such an intervention, we divided the camp into an *n* x *n* grid of squares, each with its own food line, and we replaced equation (4) with

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|  | (11) |

Here *niyd* is the number of infectious individuals without symptoms (i.e., pre-symptomatic and asymptomatic) served by the same food line as individual *i* on day *d*, and *nizd* is the total number of individuals without symptoms served by the same food line as individual *i* on day *d*. Rescaling the transmission probability by 1/*n* accounts for the fact that shorter lines have shorter waiting times. We conducted simulations with to study how the number of sectors affects COVID-19 epidemics.

*PPE*. Behavioral changes such as using personal protective equipment (PPE; e.g., facemasks), frequent handwashing, and maintaining safe distances from others may reduce the risk of COVID-19 transmission. In Moria, there is approximately one tap per 42 people, so frequent handwashing (e.g., greater than 10x per day, as in [12]) may be impossible. Due to the high population density (~20,000 people km-2), maintaining safe distances among people may also be difficult or impossible. However, people in Moria have been provided with facemasks. To simulate the wearing of facemasks, we scaled the odds of transmission per interaction in food lines, in toilet lines, and during movement about the camp by a factor of 0.32 following [12].

*Remove-and-isolate*. Managers of some populations, including Moria, have planned interventions in which people with COVID-19 infections and their households will be removed from populations and kept in isolation until the infected people have recovered. To simulate a remove-and-isolate intervention, we conducted simulations in which in each individual with symptoms (i.e., symptomatic, mild case, or severe case) is detected with probability *b* on each day. If an individual with symptoms is detected, that individual and its household are removed from the camp. Individuals removed from the camp can infect or become infected by others in their household following equation (2), but cannot infect or become infected by individuals in other households by any transmission route. We assume that individuals are returned to the camp 7 days after they have recovered, or if they do not become infected, 7 days after the last infected person in their household has recovered. We simulated remove-and-isolate interventions with . These capture interventions in which symptomatic individuals and their households are removed on average on the 1st, 2nd, or 4th day of symptoms.

*Lockdown*. Some countries have attempted to limit the spread of COVID-19 by requiring people to stay in or close to their homes [13]. This intervention has sometimes been called “lockdown.” We simulated a lockdown in which most individuals are restricted to a home range with radius *rl* around their households. We assumed that a proportion *vl* of the population violates the lockdown. Thus, for each individual in the population, we set their home range to *rl* with probability (1- *vl*). Otherwise, we set their home range to 0.2 in the high-movement scenario or to 0.1 in the low movement scenario. We simulated interventions with (*rl*, *vl*) ∈ {(0.005, 0.05), (0.01, 0.1), (0.02, 0.2)} to study lockdowns that are more or less restrictive and strictly enforced.

**Simulations**

In each simulation, we initialised the model population and camp structure as described above, and we randomly selected one individual to enter the exposed state. We simulated the epidemic by iterating days, and we tracked the disease state of each individual over time. We ran each simulation until all individuals in the population were either susceptible or recovered, at which point the epidemic had ended. We recorded the maximum number of infected individuals, the time to peak infection, and the proportion of the population that became infected in each simulation. When remove-and-isolate simulations were in place, we also recorded the peak number of individuals in isolation, to help assess the plausibility of the intervention.

Figure #. Disease progression.



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