Empowering the crowd: Feasible strategies to minimize the spread of COVID-19 in high-density informal settlements

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August 21, 2020

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Abstract

Background, Methods, Findings, Interpretation, and Funding. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

Introduction

The COVID-19 pandemic is intensifying in the developing world [1]. In Africa, SARS-CoV-2 has been spreading from urban areas to informal settlements [2]. With more than 1 billion people living in informal settlements worldwide, urgent action is needed to contain the virus in these settings, a task which necessarily involves the engagement of the communities living in them [3].

The need for action is even more pressing in regions immersed in protracted armed conflicts, where large portions of their populations have become displaced. When the displaced population exceeds official resettlement and refugee camp capacity, Internally Displaced Persons (IDPs) must live in informal settlements (hereafter named "camps"). These regions must contend with the public health challenges resulting from violence [4], the deterioration of health-systems [5], especially of critical care [6], and the breakdown of essential public infrastructure such as water and sanitation systems [7].

This study focuses on the Northwest region of Syria (NWS): a relatively small geographical area with 4.2 million people, of which 1.15 million (27.4%) are IDPs living in camps [8]. The health status of households in camps in NWS is poor; 24% have a member with a chronic disease, of whom 41% have no access to medicines [9]. As in other conflict regions, the political instability in NWS hinders coordinated public health actions, and the ongoing movements of IDPs create ample opportunity for infectious disease transmission, while making contact tracing interventions infeasible.

To investigate feasible COVID-19 prevention interventions in the camps, we considered a Susceptible-Exposed-Infectious-Recovered model in which the camps' populations are divided into classes reflecting their estimated age-structures and comorbidity prevalence (see Supplementary Table 1). We use this model to propose a number of interventions aimed at reducing the number of contacts within and between population classes in general, and with symptomatic individuals in particular. We paid special attention to how the living conditions in informal camps inform the assumptions underlying our proposed interventions. We modeled interventions previously proposed for African cities [10], such as self-distancing, isolation of symptomatic individuals and the creation of a 'safety zone' in which more vulnerable members of the population are protected from exposure to the virus.

Building upon the approach used to model the impact of these interventions in African cities, our model includes a parameterization of the contacts each individual has per day [10]. We further elaborate upon this approach by making a more explicit representation of contacts and other parameters in the model. We consider the micro-dynamics of contacts, the time that individuals take to recognize their symptoms before self-isolating, the effect of having cares to attend isolated individuals, and the existence of a buffering zone in which exposed and protected population classes can interact under certain rules, among other details. We examine a potential worst-case scenario in which there is no access to any healthcare facility. Since empowering local communities in conflict regions to understand how to control COVID-19 is possibly the most (and perhaps only) effective way to minimize its spread, our models are of utmost importance for informing the implementation of realistic interventions in these regions.

Methods

The model

We considered a discrete-time stochastic model, simulating a viral outbreak in a single camp over a 12 month period. The model is divided into compartments containing individuals at different possible stages along the disease's progression (see Supplementary Fig. 1), and splits the population into classes by age and comorbidity status. The simulation starts with a completely susceptible population where one person is exposed to the virus. The disease in exposed individuals progresses through a preclinical infectious stage, followed by either a clinical (symptomatic) or subclinical (asymptomatic) infectious stage, resolving through recovery or death. Additional susceptible individuals become infected through contact with infectious individuals. We verified that a steady state was always reached before the end of each simulation. We did not consider migration, births, nor deaths due to other causes, since they are small enough in magnitude to not significantly impact the course of an outbreak, provided additional conflict does not erupt.

Population structure

We parameterized the model with data from IDPs in NWS [11]. The population size of informal camps is log-normally distributed, with a mean of 600 individuals. We simulated camps with 500, 1000 and 2000 individuals. Since interventions tend to be less effective in larger camps, the results presented refer to simulations with 2000 individuals, unless otherwise specified. We considered 3 age groups: children (age 1, 0-12 years old), adults (age 2, 13-50 yrs.) and the elderly (age 3, >50 yrs). For ages 2 and 3, we considered two subclasses comprising healthy individuals and individuals with comorbidities. The fraction of a simulated camp's population in each of these 5 classes is shown in Supplementary Table 1.

Epidemiological severity assumptions

In NWS, there are 975 hospital and community-based treatment (CCTC) beds (1410 planned), 114 ICU beds (188 planned) and 86 ventilators available (159 planned) for 4.2 million people [12, 8]. Basic estimation predicted a collapse of the health facilities after 8 weeks of the outbreak [13]. Hence, we considered a worst-case scenario in which individuals will not have access to healthcare. We consequently assumed that all critical cases, those requiring ICU care, would die. However, there is greater uncertainty of the fate of severe cases, those requiring hospitalization but not ICU care. We therefore considered a compartment for severe cases to account for a longer infectious period if they stay in the camp. This compartment also helped us model some interventions more realistically, for example by noting that the symptoms of severe cases are incompatible with self-isolation. To estimate upper and lower bounds for the outcome variables of our model, we simulated two possible scenarios for the fate of this compartment: one in which all cases recover, and another in which all die. In the simulations presented in the Main Text, we consider the worst-case scenario in which all of these cases die.

The fractions of symptomatic cases that are severe or critical are class-specific (parameters h_i and g_i, see Supplementary Table 1). We estimated these parameters using data from developed countries with superior population health [14, 15]. Following previous work [10], we reasoned that the case severity distributions of NW Syrian adult population classes would correspond with those of older age groups in developed countries.

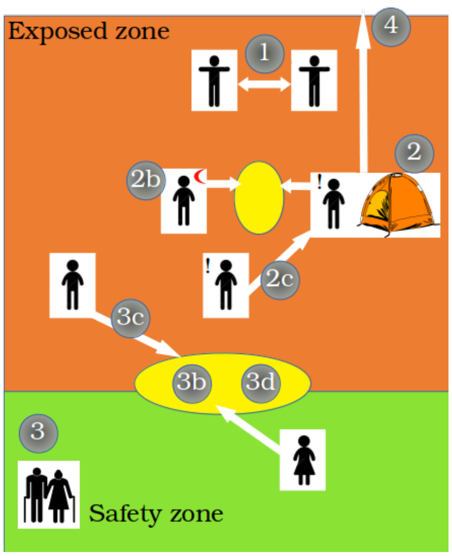
Transmissibility assumptions

We assumed presymptomatic, asymptomatic, symptomatic and hospitalized individuals were equally infectious. We obtained the duration individuals spend in each compartment from the literature (see Supplementary Table 2).

Each individual's contact rate (see Supplementary Table 1) is class-specific, and was estimated from conversations with camp managers in NWS. The probability of random interaction with an individual from each class is proportional to this class' fraction of the population. The product of these two values is the contact rate between two respective classes.

The probability of infection from contact with an infectious individual, τ, was estimated from a Gaussian distribution of the basic reproduction number, R_0, with mean of 4 (99% CI: 3–5). This distribution was a compromise between values reported in the literature from regions with high-density informal settlements: R_0=2.77 in Abuja and 3.44 in Lagos, Nigeria [16], 3.3 in Buenos Aires [17], and 5 in Rohingya refugee camps in Bangladesh [18]. The probability distribution of τ was estimated by randomly generating a value for R_0, and dividing this value by the real part of the main eigenvalue of the Next Generation Matrix (see Supplementary Material).

Interventions



	Intervention	Description	Levels
1	**Self-distancing**	Reduction of mean number of contacts per day per individual	20%, 50%
2	**Self-isolation**	Isolation of symptomatic (!) people in individual tents	Number of available tents: 10, 20, 50, 100, 250, 500, 1000, 2000
2b	Number of carers	Number of healthy people that will take care of self-isolated people	1 per tent
2c	Self-isolation delay	Time from symptom onset to self-isolation	12h, 24h, 48h
3	**Safety zone**	Designated area for vulnerable population	Elderly only, Elderly + adults with comorbidities, Elderly + adults with comorbidities + healthy adults and kids, up to 20%, 25%, or 30% of the population
3b	Number of contacts	Number of contacts people in the safety zone can have with people from the exposed zone (contacts always happen in the buffering zone)	2 or 10 contacts per week per individual residing in the safety zone
3c	Health checks	Exclude symptomatic (!) people from meeting with people from the safety zone	
3d	Lockdown of buffering zone	Lockdown if one case is detected in the population	Reduces value of 3b by 50%, or 90%
4	**Evacuation of severely symptomatic**	Evacuated individuals cannot infect other people from the camp, but they do not receive healthcare	
	Buffering zones	Open space, 2m distancing, use of face cover	Reduces probability of infection by 80%

Figure 1: Diagram of interventions.

Self-distancing

We considered a situation in which the whole population reduces their mean number of contacts per day by a certain magnitude,20% or 50% (see Fig. 1-1). Since the mean number of people per tent in a camp is 5.5 and sanitation facilities are shared [11] we inferred that the number of contacts per day cannot be reduced by more than a 50%. For an adult, this would mean 7.5 contacts per day.

Buffering zone

Since only moderate self-distancing can be achieved, additional control measures involve splitting the population into subgroups occupying different zones of the camp, limiting cross-group contact to specified locations, or "buffering zones". We envision these zones as open spaces, with guidelines in place to limit occupancy to 4 individuals wearing masks, with 2 meters separating individuals from the two separate zones. We assume that non-compliance will be such that the probability of transmission from contacts will be reduced by 80% compared to the baseline (see Fig. 1).

Self-isolation

Self-isolation is a challenge in informal settlements, where households consist of a single (often small) space, water is collected at designated locations, sanitation facilities are communal and food supplies are scarce. We considered the possibility of those showing symptoms self-isolating in individual tents in dedicated parts of the camps, or next to the tents of their relatives. We simulated this intervention with 10 isolation tents per camp, up to 2000 (see Fig. 1-2). In addition, we modeled the role of carers dedicated to supplying isolated individuals, who interact with them via a buffering zone (see Fig. 1-2b). In considering one care-giver per individual with one contact per day, we do not neglect their probability of infecting the rest of the camp. We further considered that severe cases, or those in the hospitalized compartment, are fully infectious since they require more intensive care that is not possible to deliver while adhering to the guidelines of the buffering zone. We also considered minimum time intervals for individuals to recognize their symptoms: with means of 12, 24 and 48 hours (see Fig. 1-2c).

Safety zone

In this intervention, the camp is divided in two areas: a safety zone, in which more vulnerable people live (hereby referred to as a "green" zone following previous studies [10]), and an exposed ("orange") zone with the remaining population. In our simulations, the first exposed individual always belongs to the orange zone. We avoided the use of the term "shielding" to describe this intervention, since it may erroneously suggest that the vulnerable population is isolated in a closed space, such as a separated building. Such an intervention would require additional assumptions on how contacts occur in a closed space. The living conditions within both zones remain the same, so the overall contact rate does not change unless self-distancing is also implemented. In practice, reducing the contact rate with individuals living in a different zone implies an increase in the contact rate with individuals in the same zone (see Supplementary Material). This allows us to investigate undesired side-effects of this intervention. Since proposals for partitioning the population may be received differently across camps, we considered several scenarios for allocating a camp's population to the two zones (see Fig. 1-3, Supplementary Table 3). We consider the scenario in which all the elderly, adults with comorbidities and their family members up to 20% of the camp's population live in the green zone in the Main Text, unless otherwise specified.

Interaction between the two zones is limited to a buffering zone. If individuals in the green zone cannot leave and thus need to be provided with supplies by individuals in the orange zone, any delivery of supplies will necessarily take place in the buffering zone. In our simulations, we considered limiting individuals in the green zone to 10 or 2 contacts with individuals from the orange zone per week (see Fig. 1-3b). Other variations on this intervention we explored include preventing symptomatic individuals from entering the buffering zone (see Fig. 1-3c) and "locking down" the green zone, where their number of weekly contacts in the buffering zone is reduced by 50% or 90% (see Fig. 1-3d).

Evacuation

The last intervention we simulated is the evacuation of individuals in the hospitalization compartment. We assume the evacuees will be taken to isolation centers, not hospitals, so this measure does not change their fate [12]; the only effect this intervention has is reducing the infectivity of evacuees to zero (see Fig. 1-4).

Analysis of the interventions

For each implementation of the interventions, we ran 500 simulations, and compared results between them. The main variables considered are the fraction of simulations in which at least one death is observed, a proxy for the probability of an outbreak, the fraction of the population that dies and the time until the symptomatic population peaks, as well as the case fatality rate (CFR) and the fraction of population that recovers. For consistency, we only considered simulations in which there was an outbreak when comparing the outcome of a variable between interventions. For pairwise comparisons between interventions, we used Student's t-tests for variables with equal variance and Welch's t-tests for variables with unequal variance. For multiple comparisons across non-orthogonal variables, we used Tukey's tests.

Results

Without any interventions, the mean CFR is ~2% in simulations where all severe cases requiring hospitalization recover (see Supplementary Fig. 2), and ~11% in simulations where all severe cases die. We consider the latter scenario to evaluate the interventions. In this scenario, the probability of observing an outbreak is close to 0.85, in which ~10% of the camp dies, the number of symptomatic cases peaks after 55 days and ~84% of the population recovers.

Self-distancing has a notable effect on reducing the probability of an outbreak; even a 20% reduction in daily contacts is associated with a ~10% decrease in outbreak probability (see Fig. 2A). A greater reduction in daily contacts, of 50%, is required to observe a significant decrease, of as much as 35%, in the fraction of the population dying (see Fig. 2B). A reduction in contacts of this magnitude also significantly extends the time until the number of symptomatic cases peaks to 110 days, roughly double the time when no interventions are in place (see Fig. 2C). However, the proportion of the population recovered after 12 months is reduced by ~30% (see Supplementary Fig. 3).

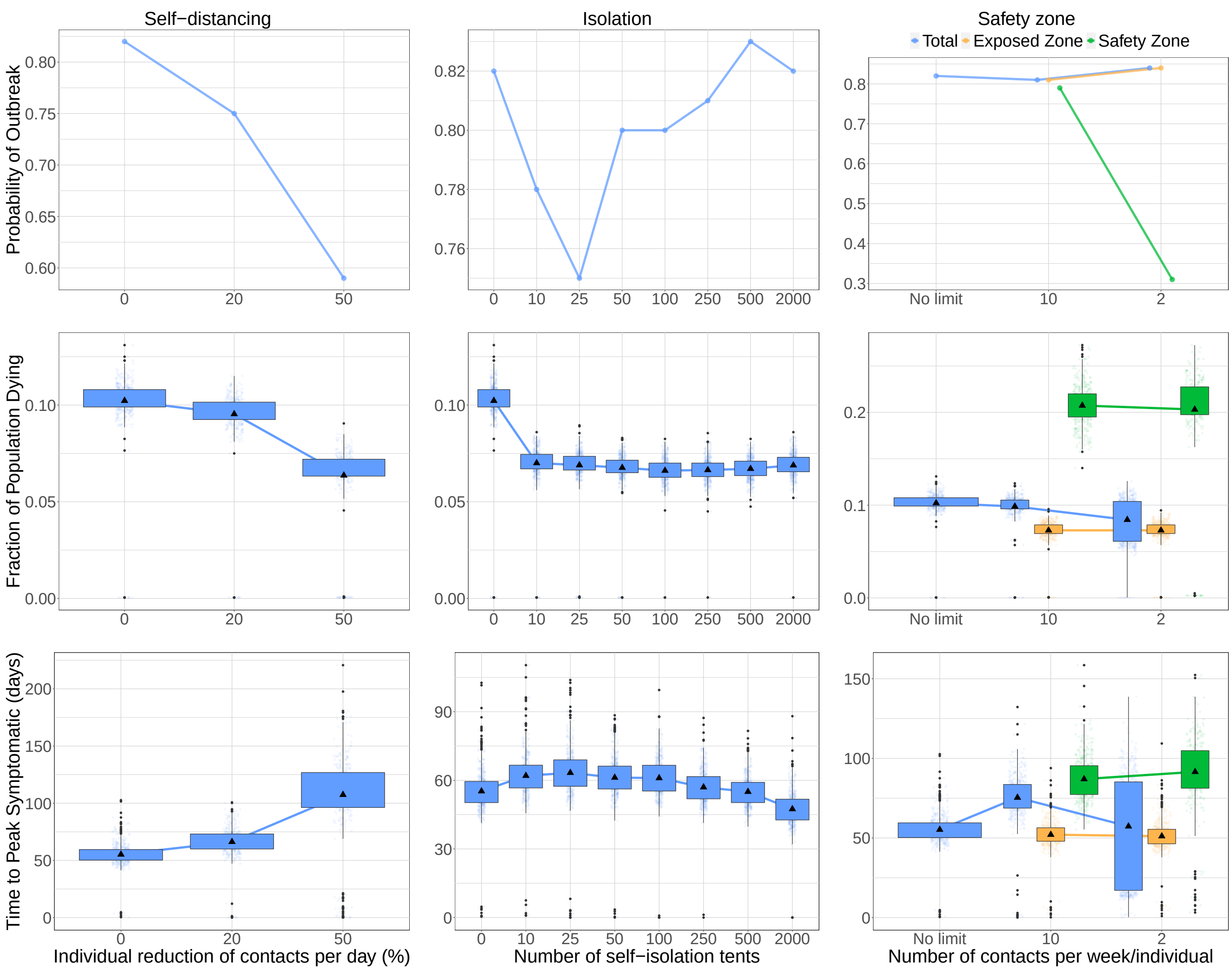


Figure 2: **Effect of interventions on outbreak probability, fatalities and time until synptomatic cases peak.** A: Self-distancing, probability of an outbreak. B: Self-distancing, fraction of the population dying. C: Self-distancing, time until peak symptomatic cases. D: Self-isolation, probability of an outbreak. E: Self-isolation, fraction of the population dying. F: Self-isolation, time until peak symptomatic cases. G: Safety zone, probability of an outbreak. H: Safety zone, fraction of the population dying. I: Safety zone, time until peak symptomatic cases.

With only 10 tents for a camp of 2000 people (i.e. 1 tent for every 200 people), self-isolation yields a modest decrease in the probability of observing an outbreak (see Fig. 2D), but a stronger reduction in the fraction of the population dying (~30%) (see Fig. 2E). However, further increasing the number of tents does not significantly augment this reduction, and when the number of tents surpasses 1 per every 10 people, fatalities even begin to slightly increase again. This effect is a consequence of having one carer per individual isolated (see Supplementary Material), so when the isolated (infected) population increases, the number of healthy adults in contact with them increases in tandem. Nevertheless, we observe a continuous, albeit small, reduction in CFR with an increasing number of tents (see Supplementary Fig. 4).

Instrumentally, the potential reductions in overall fatalities and CFR from self-isolation are realized whether the time required for individuals to recognize their symptoms is 12h or 24h on average, but the intervention becomes less effective when this time increases to 48h (see Supplementary Fig. 5). We observe no significant effects when severe cases requiring hospitalization are evacuated (see Supplementary Fig. 6). Since we assume that evacuation does not change their fate, this intervention only affects their infectivity. Although the period between developing more severe symptoms and dying is relatively long (~10 days), the number of individuals under these conditions is only a small fraction of the total infectious population at any given time.

Creating a green zone improves the effect of previous interventions overall, but with sometimes opposite outcomes for the exposed and protected populations. For example, the probability of an outbreak sharply decreases for the protected population, by almost 60%, but only if two contacts are allowed per week in the buffering zone (see Fig. 2G). Notably, most of this reduction is only achieved when health-checks excluding symptomatic individuals from the buffering zone are in place (see Supplementary Fig. 7). On the other hand, the probability of an outbreak may slightly increase for the exposed population, a consequence of the relative increase in intra-zone contacts. Despite this side-effect, by shifting the burden of an outbreak towards the less vulnerable population in the orange zone, this intervention not only reduces fatalities among the more vulnerable population in the green zone (see Supplementary Fig. 8), but also reduces the overall CFR (see Supplementary Fig. 9) and thus the number of fatalities globally (see Fig. 2H). Another important outcome of this intervention is the notable increase in time until the number of symptomatic cases peaks, an effect that is observed globally, but especially so in the protected population (see Fig. 2I).

Considering different scenarios for allocating people to the green zone, the lowest probability of an outbreach is achieved when only the elderly or at most the elderly and adults with comorbidities move there (see Supplementary Fig. 10). Positive effects of the green zone intervention are even more marked in camps with smaller populations, for every outcome of interest except time until symptomatic cases peak (see Supplementary Fig. 11). The incorporation of a lockdown has the greatest effect on reducing the probability of an outbreak in the green zone, to under .10. While lockdowns show no positive effect on green zone fatalities in the few instances where an outbreak does reach there, they decrease CFR and overall fatalities by further concentrating outbreaks in the less vulnerable population (see Supplementary Fig. 12).

The effects of the interventions observed when we examine them individually build upon each other when multiple interventions are implemented in tandem (see Fig. 3). The protective effects of the safety zone intervention especially are most fully realized when paired with other interventions, less so when implemented on its own. When all interventions are implemented together: moderate self-distancing (50% reduction in contacts), self-isolation of symptomatic cases (1 tent for every 40 people), a safety zone with 2 contacts per week in the buffering zone, health checks and a moderate lockdown (50%), and evacuation of severe cases, fatalities are reduced by ~80%.

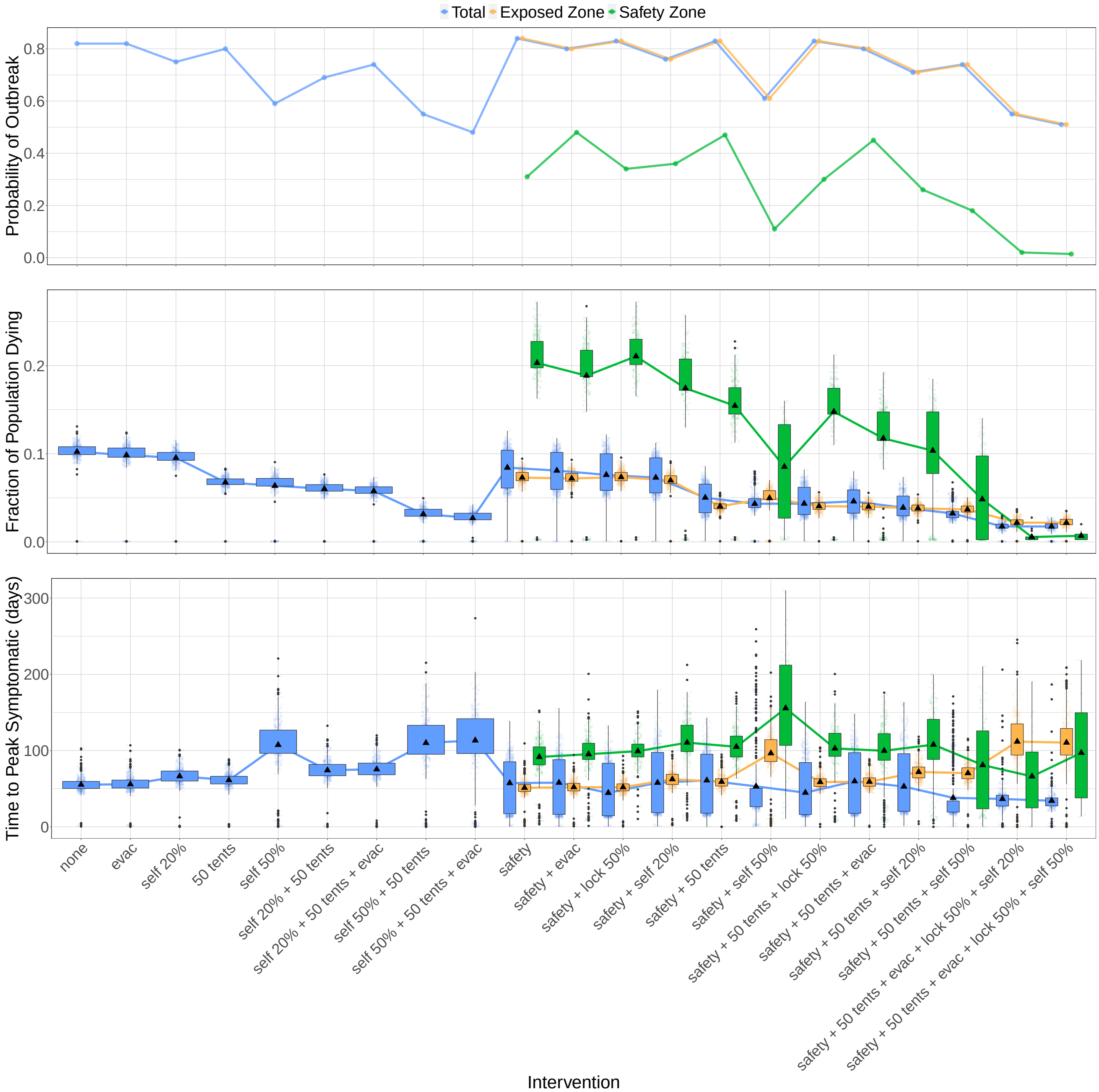


Figure 3: **Combinations of interventions.** Probability of an outbreak (top), fraction of the population dying (middle) and time until peak symptomatic cases (bottom) for different combination of interventions. Evac = evacuation of severely symptomatic, self = self-distancing, tents = number of available self-isolation tents, safe = safety zone, lock = lockdown of buffering zone. For combinations of interventions including a safety zone, we distinguish between the population living in the green zone, in the orange zone and the whole population.

Discussion

In this study, we propose a number of interventions of immediate applicability to informal settlements. We focused on IDP settlements in NW Syria, taking into account the interventions' feasibility, cultural acceptance and their need for low-cost. When confronted with different possible scenarios, we generally considered the worst-cases, highlighting the interventions most effective in the direst conditions but possibly resulting in an overestimate of the number of deaths. Our results align with previous simulation studies of potential COVID-19 interventions in similarly densely populated, low resource settings where informal settlements are present, such as urban areas of sub-Saharan Africa. In these settings, social-distancing is demonstrated to be an effective intervention, and even small changes are estimated to have large effects on outbreaks [19], in some cases determining whether or not already inadequate healthcare systems become overwhelmed [20]. Zandvoort et al. show that similar measures to the ones we consider: self-isolation, physical distancing and "shielding" the vulnerable, may reduce mortality by 60%-75% in African cities [10].

Self-distancing proves to be an effective measure in our models as well; reducing contacts by 50% has the greatest effect across the most outcomes of interest of any of the interventions we examined. However, the difficulty of achieving a reduction of this magnitude cannot be overlooked, especially considering the large proportion of the population composed of children, a group with an already high contact rate that may prove difficult to control [11].

We also propose self-isolation using individual tents which can be located in a dedicated zone or next to the tents of relatives, where contact with non-isolated individuals is mediated by a buffering zone. This intervention is effective with even a small number of isolation tents, as low as 5-10 tents per 1000 camp residents. After conversations with camp managers, we found that this intervention is more likely to be accepted in NW Syria than evacuation to community-based isolation centers. Community-based isolation not only poses cultural challenges; the capacity required to implement it has hardly been met [12].

One of the key parameters we assessed for the implementation of self-isolation is the need for carers. In considering one carer per isolated individual, with daily contact in a buffering zone, once a certain threshold of isolated cases (~200 per camp of 2000) is surpassed, the benefits of isolation begin to be outweighed by an increase in infectivity resulting from a growing number of exposed carers. This pitfall could be circumvented through the creation of a more organized group of carers, thus reducing the number of healthy adults in contact with isolated (infectious) individuals.

Much of the success or failure of the safety zone intervention hinges on the functioning of the buffering zone. The number of inter-zone contacts per week, the implementation of health checks, and potential lockdowns all have notable effects. Also important is the portion of the population that is protected; protecting only the vulnerable may have the most beneficial effects, but it is precisely these vulnerable individuals, the elderly and people with comorbidities, who may most need family members to care for them. While safety zone scenarios that allow greater numbers of family members to accompany their vulnerable relatives to the green zone may confer greater epidemiological risk, they may also engender greater well-being and social cohesion.

Although setting up a safety zone sharply reduces the probability of an outbreak in the population classes with the highest CFRs, thus reducing the CFR of the entire population, it is possible that our model may overestimate mortality from an outbreak in the green zone in the few instances when there is one. Since total numbers of contacts are conserved in our modelization, individuals do not reduce their contacts when moved to the green zone. While contacts may be roughly conserved by those in the orange zone in practice, this is less likely in the green zone. If the green zone is set up for a capacity of 20% of the camp's population, vulnerable individuals will be instructed by camp managers to bring 1, or perhaps 2, family members with them, so we expect households will be smaller than their typical average size of 5.5 [11]. Smaller households should result in fewer contacts, and thus less severe green zone outbreaks. In order to change our assumption that contacts in the safety zone intervention are conserved, we would need data from camp managers on household sizes in the green zones once they are set up.

An instrumental consideration for our models is the fraction of the population recovered from COVID-19 after a steady state is reached. Although the duration for which SARS-CoV-2 infection confers immunity is uncertain, the proportion of the population recovered after an outbreak should play a role in its protection against future ones. For every intervention except self-distancing of 50%, we observed that the fraction of population recovered meets or exceeds 75%. This is quite promising to prevent future outbreaks.

Unaccounted for social and cultural dynamics will undeniably complicate the feasibility of our proposed interventions. But one example we have not addressed here is the unlikeliness of a child under 13 self-isolating, yet there are undoubtedly countless others we have not considered. Nevertheless, if the dynamics of the virus are well understood by local communities and at least some of the interventions we propose are implemented, the impacts of COVID-19 can be mitigated even in an environment as challenging as NW Syria. Our results demonstrate that a community-based public health approach to controling COVID-19 can be effective, especially in a context where governmental and health system capacity for responding to public health crises is severely limited. Given a rapidly changing environment and slow responses of local and international authorities, empowering local communities themselves is perhaps the best, if not the only way, to help them avoid the worst consequences of the pandemic. This not only applies to IDP camps in NW Syria, but to conflict-torn regions, informal settlements and vulnerable communities around the world: from the urban slums of India, townships of South Africa and favelas of Brazil, to the refugee camps of Kenya, Bangladesh and South Sudan; the low-cost, effective interventions we present are feasible, needed and urgent.

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