

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

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Abstract

More than 1 billion people live in informal settlements worldwide, where precarious living conditions pose unique challenges to managing a COVID-19 outbreak. Taking Northwest Syria as a case-study, we simulated an outbreak in high-density informal Internally Displaced Persons (IDP) camps using a stochastic Susceptible-Exposed-Infectious-Recovered model. Expanding on previous studies, taking social conditions and population health/structure into account, we modeled several interventions feasible in these settings: moderate self-distancing, self-isolation of symptomatic cases, and protection of the most vulnerable in “safety zones”. We considered complementary measures to these interventions that can be implemented autonomously by these communities, such as buffer zones, daily health-checks, and carers for isolated individuals, quantifying their impact on the micro-dynamics of disease transmission. All interventions significantly reduce outbreak probability and mortality. Self-distancing reduces mortality by up to 35% if contacts are reduced by 50%. A similar reduction in mortality can be achieved by providing 1 self-isolation tent per 200 people. Protecting the most vulnerable in a safety zone has synergistic effects with the other interventions and reduces mortality in the most vulnerable population. Our model predicts that a combination of all simulated interventions may reduce mortality by as much as 80% and delay an outbreak’s peak by more than three months. Our results highlight the potential for non-medical interventions to mitigate the effects of the pandemic. Similar measures may be applicable to controlling COVID-19 in other informal settlements, particularly IDP camps in conflict regions, around the world.

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. We use this model to propose various 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 carers to attend to isolated individuals, and the existence of a buffer zone in which exposed and protected population classes can interact under certain rules. 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.

Results

We considered a discrete-time stochastic model, simulating a viral outbreak in a single camp over a 12-month period (see Materials and Methods). In NWS, there are 4 active and 2 planned COVID-19 referral hospitals, with a current capacity of 66 ventilators, 74 ICU beds and 355 ward beds for 4.2 million people [11, 12]. Basic estimation predicted a collapse of health facilities 8 weeks into an outbreak [13]. Hence, we considered a worst-case scenario in which individuals will not have access to healthcare and assumed that all critical cases (those requiring ICU care) would die. We simulated two possible scenarios for the fate of severe cases (those requiring hospitalization but not ICU care): one in which all cases recover, and another in which all die. In the absence of interventions, the mean IFR is $\sim 2\%$ in simulations where all severe cases requiring hospitalization recover (see Supplementary Fig. 2), and $\sim 11\%$ in simulations where all severe cases die. We consider the latter scenario to evaluate the effect of non-medical preventive interventions. In this scenario, the probability of observing an outbreak is close to 0.85, in which $\sim 10\%$ of the camp dies, the number of symptomatic cases peaks after 55 days and $\sim 84\%$ of the population recovers.

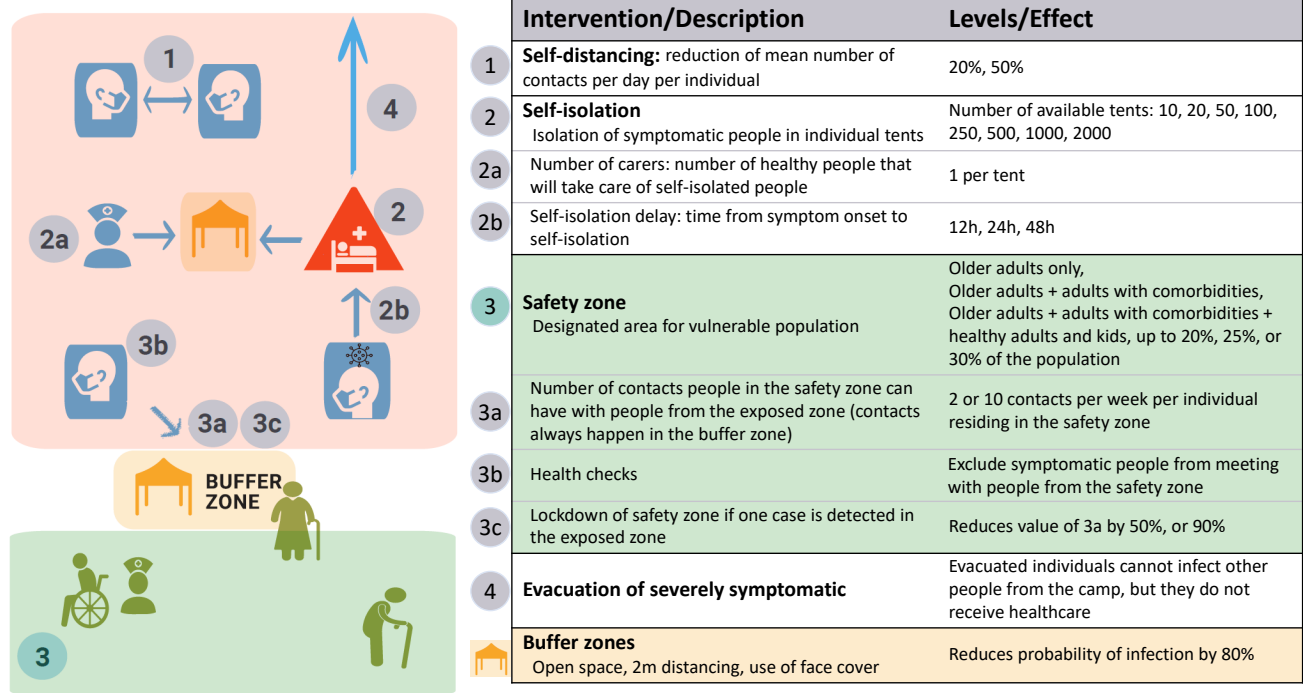


Figure 1: **Diagram of interventions.**

Self-distancing

The first non-medical intervention that we modeled is a reduction in the mean number of contacts per individual per day for the whole camp population (see Fig. 1-1). Each individual's contact rate (see Supplementary Table 1) is age group-specific and was estimated from conversations with camp managers in NWS. Since the mean number of inhabitants per tent in a camp is 5.5 and sanitation facilities are shared [14], we inferred that the number of contacts per day cannot be reduced by more than 50%. For a younger adult, this would mean 7.5 contacts per day.

Our results show that self-distancing has a notable effect on reducing the probability of an outbreak: a 20% reduction in daily contacts is associated with a $\sim 10\%$ decrease in outbreak probability (see Fig. 2A). A greater reduction in daily contacts, of 50%, is required to observe a significant decrease in mortality, of as much as 35% (see Fig. 2B). Self-distancing also significantly extends the time until the peak of the outbreak, from 55 days when there is no intervention to 110 days when contacts are reduced by 50% (see Fig. 2C). However, the proportion of the population recovered after 12 months is reduced by $\sim 30\%$ (see Supplementary Fig. 3).

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. We simulated this intervention with various numbers of isolation tents per camp, ranging from 10 to 2000 for a camp of 2000 people (see Fig. 1-2). In addition, we modeled the role of carers dedicated to providing for isolated individuals (see Fig. 1-2a). Interactions between carers and isolated individuals were restricted to buffer zones, which we envisioned as open spaces, with guidelines in place to limit occupancy to 4 individuals wearing masks, with 2 meters separating individuals, where the probability of transmission is reduced by 80% (see Supplementary Material). In considering one carer per isolated individual with one contact per day, we do not neglect their probability of infecting the rest of the camp. We also considered minimum time intervals for individuals to recognize their symptoms: with means of 12, 24 and 48 hours (see Fig. 1-2b).

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 mortality ($\sim 30\%$)

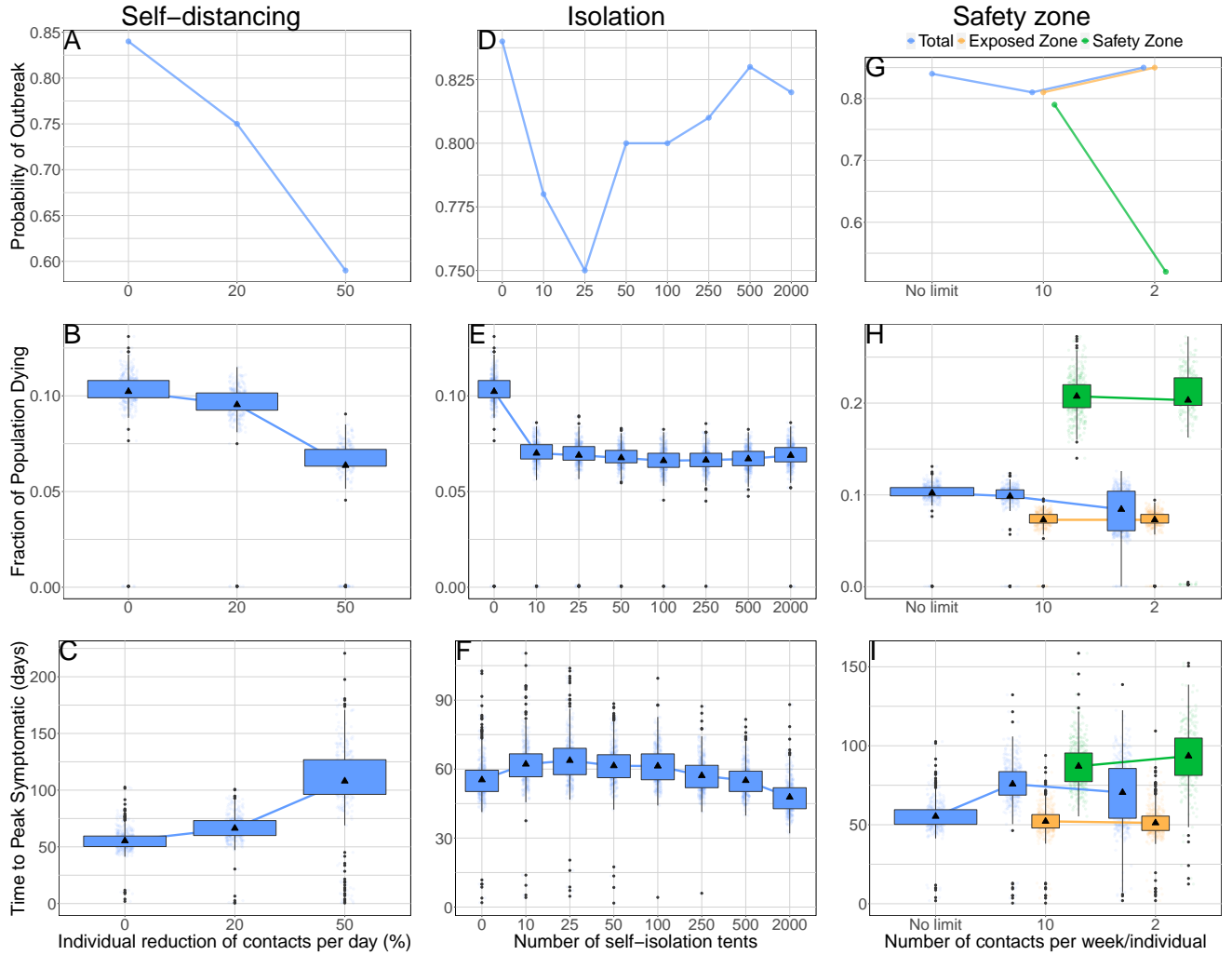


Figure 2: Effect of interventions on outbreak probability, fatalities and time until symptomatic cases peak. A: Self-distancing, probability of an outbreak. B: Self-distancing, fraction of the population dying. C: Self-distancing, time until peak symptomatic cases. D: Self-isolation, probability of an 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. Note that in figures of the safety zone intervention (panels G-I), the mean of an outcome for the whole population is not the weighted mean of the exposed and safety zones, since outcomes are computed considering simulations in which at least one death was observed in the population class inhabiting the zone. This explains why in panel I there is a reduction in the mean time until symptomatic cases peak when moving from 10 to 2 contacts per week for the whole population, despite there being an increase in the safety zone: in ~35% of simulations there is an outbreak in the orange zone but not in the green zone (panel G).

(see Fig. 2E). Further increasing the number of tents significantly augments this reduction until there is 1 per every 20 people (Kruskal-Conover post-hoc-test, $p\text{-val} < 3 \times 10^{-5}$). However, mortality begins to slightly increase again after this threshold. This effect and the increase in the probability of observing an outbreak are consequences of having one carer per individual isolated (see Supplementary Material), so when the isolated (infected) population increases, the number of healthy younger adults in contact with them increases in tandem. Similarly, we observe a reduction in IFR when increasing the number of tents up to 1 per every 20 people, and no significant reduction over that number (see Supplementary Fig. 4). Importantly, the potential reductions in overall fatalities and IFR 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).

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. 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 population to the two zones (see Fig. 1-3, Supplementary Table 3). In this section, we consider the scenario in which all older adults, younger adults with comorbidities and their family members up to 20% of the camp population live in the green zone, unless otherwise specified. Interactions between the two zones are limited to a buffer zone. Individuals in the green zone cannot leave and thus need to be provided with supplies by individuals in the orange zone. Delivery of supplies will take place in the buffer 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. 1-3a). Other variations of this intervention we explored include preventing symptomatic individuals from entering the buffer zone (see Fig. 1-3b) and a “lockdown” of the green zone, where the number of weekly contacts in the buffer zone is reduced by 50% or 90% (see Fig. 1-3c).

Creating a green zone improves the effect of the previous interventions overall, but with sometimes opposite outcomes in the exposed and protected populations. For example, the probability of an outbreak sharply decreases for the protected population, by almost 40%, if only two contacts are allowed per week in the buffer zone (see Fig. 2G). Notably, most of this reduction is only achieved when health-checks excluding symptomatic individuals from the buffer 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 (Kruskal-Wallis test, $p\text{-val} < 10^{-15}$; see Supplementary Fig. 8), but also reduces the overall IFR (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 for the vulnerable population (see Fig. 2I).

Considering different scenarios for allocating people to the green zone, the lowest probability of an outbreak is achieved when only older adults or at most older adults and younger 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 0.10 when contacts in the buffer zone are reduced by 90%. While lockdowns show no positive effect on green zone fatalities in the few instances where an outbreak does reach there, they decrease IFR and overall fatalities by further concentrating outbreaks in the less vulnerable population (see Supplementary Fig. 12).

Evacuation

The last intervention we simulated is the evacuation of severe cases (individuals in the hospitalization compartment). Since they require more intensive care that cannot be delivered while adhering to the guidelines of a buffer zone, severe cases were assumed to be fully infectious and not able to self-isolate. Once severe cases are evacuated,

their infectivity is reduced to zero (see Fig. 1-4). The fate of severe cases is not altered by this intervention since we assumed that hospitals are saturated and that evacuees are transferred to isolation centers instead.

We observe no significant effects when severe cases requiring hospitalization are evacuated (see Supplementary Fig. 6). 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.

Combined interventions

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 and Supplementary Fig. 13). The protective effects of the safety zone intervention especially are most fully realized not when implemented on its own, but when paired with other interventions. They become so effective that outbreaks in the green zone become exceptionally rare, but so well controlled when they do happen, that the majority of outbreaks see fewer than 20 cases. This leads to an anomalous increase in IFR in some of the most effective interventions, driven by the discretization of the values it can take (Supplementary Table. 4). When all interventions are implemented together: strict 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 buffer zone, health checks, a strict lockdown (90%), and evacuation of severe cases, mortality is reduced by $\sim 80\%$.

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 that are most effective in the direst conditions, but possibly resulting in an overestimate of mortality. 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 [15], in some cases determining whether or not already inadequate healthcare systems become overwhelmed [16]. 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 most outcomes of interest in 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 [14].

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 buffer 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 buffer 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, dedicated group of carers, thus reducing the number of healthy younger adults in contact with isolated (infectious) individuals.

Much of the success or failure of the safety zone intervention hinges on the functioning of the buffer 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, older adults and people with comorbidities, who may most need family members to care for them. While safety zone scenarios that allow

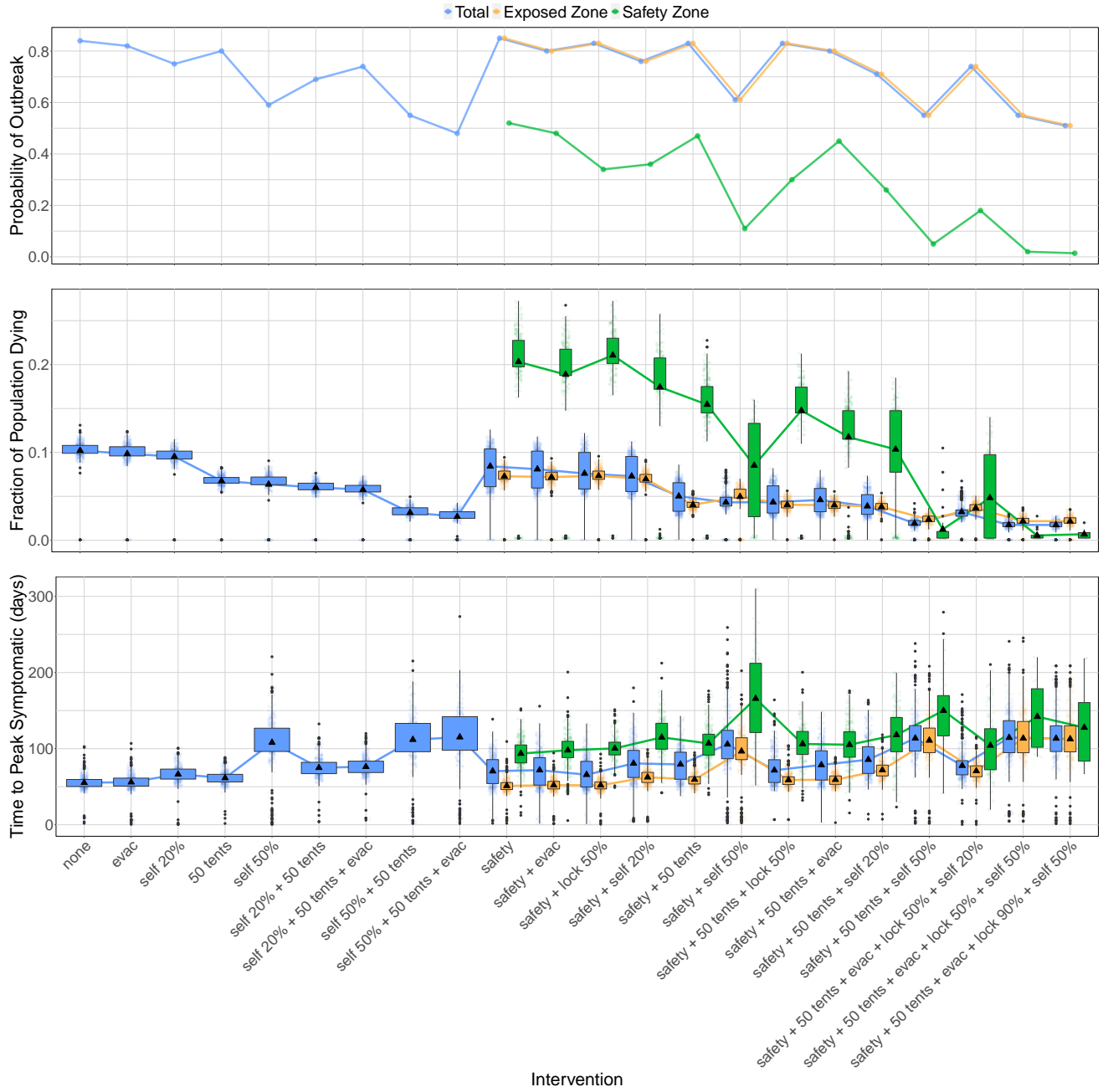


Figure 3: **Combinations of interventions.** Probability of an outbreak (top), fraction of the population dying (middle) and time until peak symptomatic cases (bottom) for different combination of interventions. Evac = evacuation of severely symptomatic, self = self-distancing, tents = number of available self-isolation tents, safety = safety zone, lock = lockdown of the buffer 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.

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 IFRs, thus reducing the IFR 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, which implies an increase in the number of contacts between vulnerable individuals. Despite this increase in contacts, we observed a significant reduction in mortality in the vulnerable population when the safety zone is implemented. These results address concerns raised around this type of intervention from previous experiences with large numbers of fatalities registered in nursing-homes in developed countries [17]. While in developed countries nursing home residents have more contacts, both with other vulnerable people (other nursing home residents) and healthy adults who live in different households (health aids), than the elderly who live at home, vulnerable people in our proposed green zone have the same number of total contacts as they would under normal conditions, but significantly fewer contacts with healthy adults from different households.

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 the population recovered meets or exceeds 75%. This is quite promising in preventing future outbreaks.

Unaccounted for social and cultural dynamics will undeniably complicate the feasibility of our proposed interventions. Only one example we have not addressed here is the unlikeliness of children under 13 self-isolating. Although the number of challenges to implementing our proposed interventions are potentially endless, the community-based nature of our approach may help circumvent these challenges much faster than healthcare-based interventions, which often depend on complex political decisions and may take years to build the requisite capacity for an effective response. 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.

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 more generally to refugee camps in conflict-torn regions, and potentially other informal settlements and vulnerable communities around the world: the low-cost, effective interventions we present are feasible, needed and urgent.

Materials and methods

The model

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 [14]. The population sizes of informal camps are approximately log-normally distributed, with a mean of 1212. We simulated camps with populations of 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), younger adults (age 2, 13-50 yrs) and older adults (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

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 about 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 [18, 19]. 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, following an implementation similar to the one proposed by Gatto et al. [20], 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 a 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 [21], 3.3 in Buenos Aires [22], and 5 in Rohingya refugee camps in Bangladesh [23]. 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).

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 infection fatality rate (IFR) and fraction of the population that recovers. For consistency, we only considered simulations in which there was an outbreak when comparing the outcome of a variable between interventions. We used the Shapiro-Wilk test [24] to verify that our results do not exhibit normally distributed residuals, Kruskal-Wallis test for pairwise comparisons [25], and Conover-Iman test for multiple comparisons [26]. The model and all statistical analyses were implemented in R; we used the package PMCMRplus [27]. All the code and results are freely available at the url <https://github.com/crowdfightcovid19/req-550-Syria>.

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Declarations

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Conflicts of interest/Competing interests

Alberto Pascual-García is a Board Member of crowdfightCOVID19, an initiative from the scientific community to put all available resources at service of the fight against COVID-19. Chamsy Sarkis (co-author) is a Board Member of the Pax Syria Foundation, a non-profit organization set up for social and philanthropic purposes including promoting and providing support and assistance to civilian aid projects in the fields of education, health, emergency assistance, psychological assistance and humanitarian aid for people affected by wars or humanitarian crises. These organizations had no role in study design, data collection, data analysis, data interpretation, or writing of the article.

Ethics approval

This study used only publicly available aggregate data and was thus not subject to ethical review.

Consent to participate

NA

Consent for publication

All authors agreed on publication.

Availability of data and material

All results are available at the url <https://github.com/crowdfightcovid19/req-550-Syria>

Code availability

All the code is freely available at the url <https://github.com/crowdfightcovid19/req-550-Syria>

Authors' contributions

All authors contributed to the conceptualization. Design of the methodology: APG, ECF, JV, JK. Formal analysis: APG, ECF, JK. Code development APG, ECF, JK. Conducted research: APG, ECF, JV, JK. Validate results: APG, ECF, JK, JV. Contributed resources: APG, CS, ECF, JK. Data curation: APG, JK. Visualization: APG, ECF, JK. Writing (original draft) APG, ECF, JK. All authors contributed to the final version of the manuscript, and APG supervised the research.

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